Simulation based forward modeling of galaxy populations

Alex Alarcon
Junior Leader Fellow 'la Caixa'
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In collaboration with:

Andrew Hearin

Gillian Beltz-Mohrmann

Matt Becker

Jonas Chaves-Montero

Alan Pearl

Differentiable sky predictions

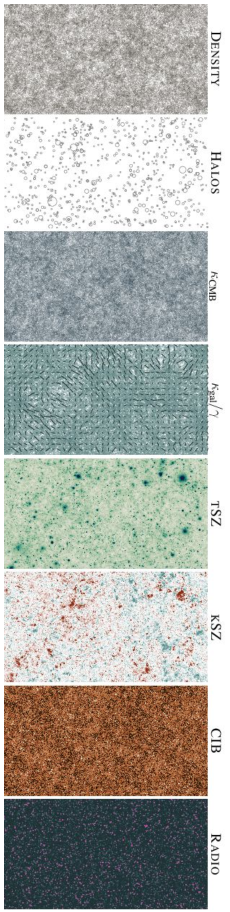
Diffmah (halo mass)
Diffprof (halo concentration)

Diffstar (galaxy in-situ star formation history)
Diffburst (galaxy starbursts)

DSPS (composite stellar populations)
Diffdust (dust attenuation)

Diffmerge (galaxy merging)

Multi-λ predictions



Inset image credit: Millennium XXL simulation, NASA, ESA, Yuuki Omori/Agora simulation

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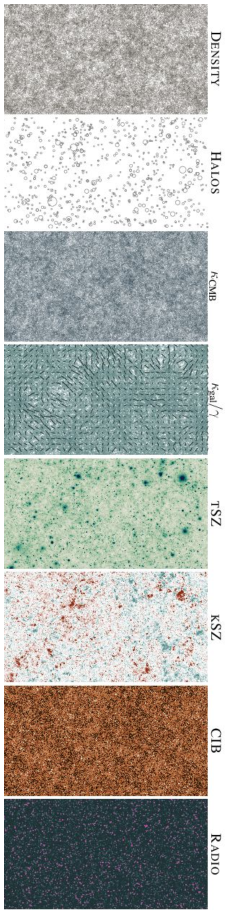

- Building **ground-up reformulation** of galaxy–halo connection.

Inset image credit: Millennium XXL simulation, NASA, ESA, Yuuki Omori/Agora simulation

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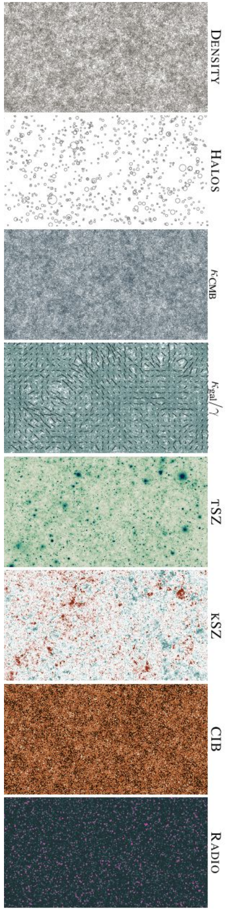

- Building **ground-up reformulation** of galaxy–halo connection.
- We seek to identify the **minimum but interpretable** parametric flexibility that is required to accurately capture the data.

Inset image credit: Millennium XXL simulation, NASA, ESA, Yuuki Omori/Agora simulation

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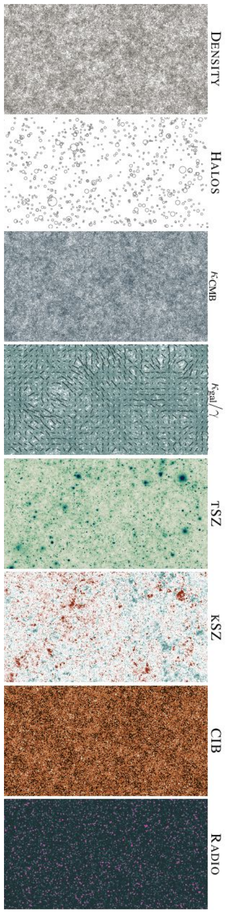

- Building **ground-up reformulation** of galaxy–halo connection.
- We seek to identify the **minimum but interpretable** parametric flexibility that is required to accurately capture the data.
- Models become **automatically differentiable** thanks to their implementation in JAX.

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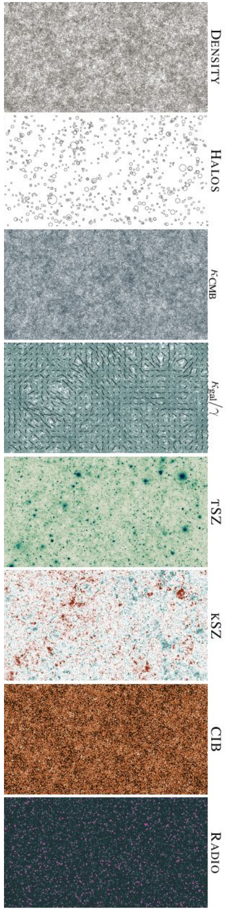

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Diffmah: 2105.05859

Diffmah: Halo Mass Assembly

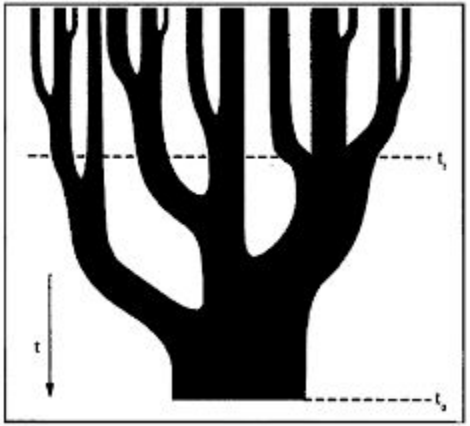
Diffmah is a parametric model for halo mass assembly.

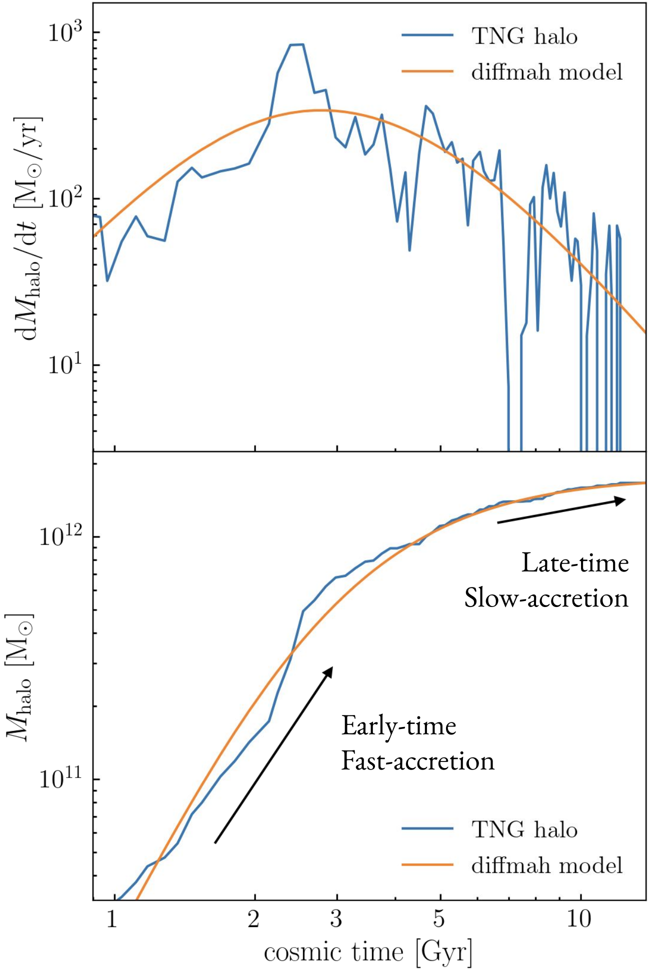
The base is a high resolution N-body simulation with merger trees.

Each halo in the simulation is then replaced by a best-fitting 4 parameter formula:

$$M_{\rm halo}(t) = M_0(t/t_0)^{\alpha(t)}$$

Power law with a rolling index





Differentiable sky predictions

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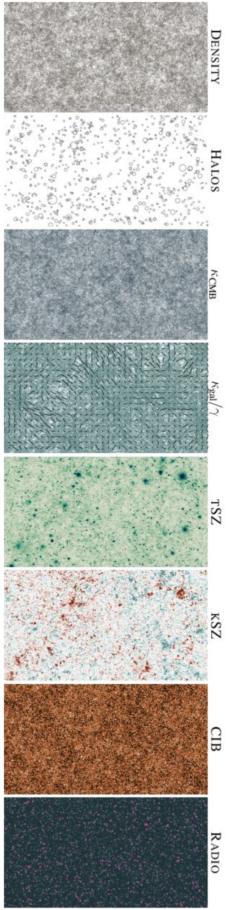

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Diffstar: Gas and halo mass assembly

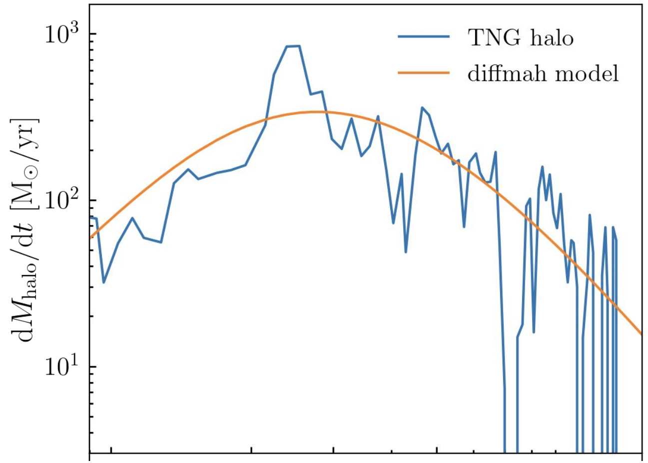
The Diffstar model assumes that baryonic matter becomes available for star formation at a rate that is closely related to the growth rate of the dark matter halo:

$$\frac{\mathrm{d}M_\mathrm{g}}{\mathrm{d}t} = f_\mathrm{b}\frac{\mathrm{d}M_\mathrm{h}}{\mathrm{d}t}$$

Gas accretion rate → $\frac{\mathrm{d}M_\mathrm{g}}{\mathrm{d}t}$

cosmic baryon fraction → f_b

Mass accretion rate → $\frac{\mathrm{d}M_\mathrm{h}}{\mathrm{d}t}$



Diffstar: 2205.04273

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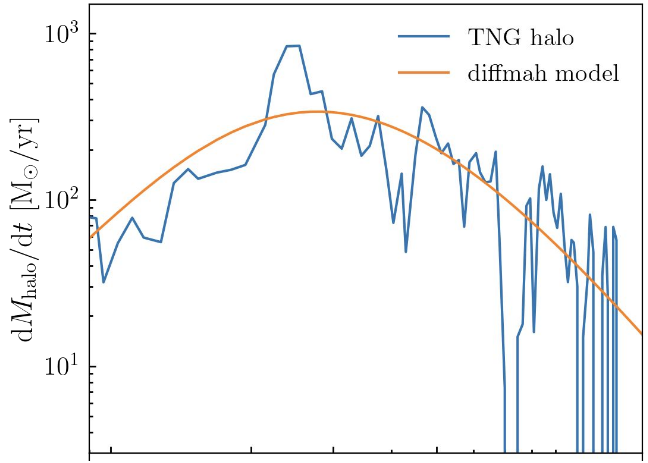
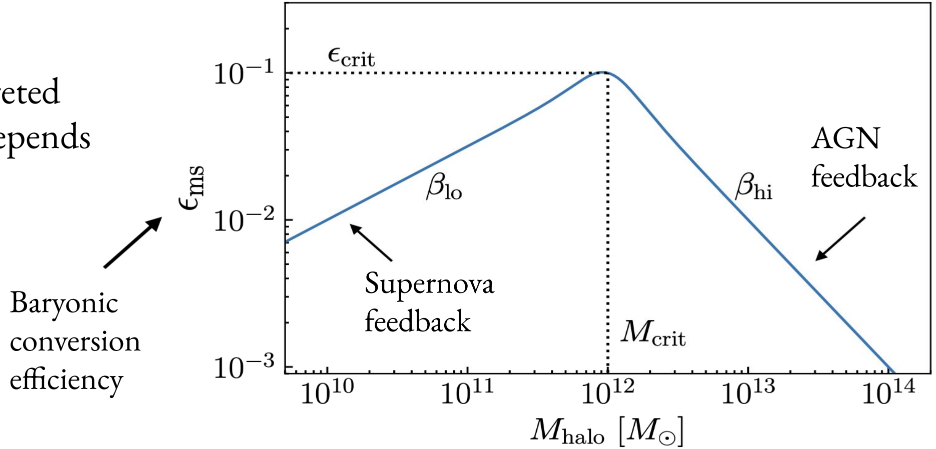
Gas accretion rate

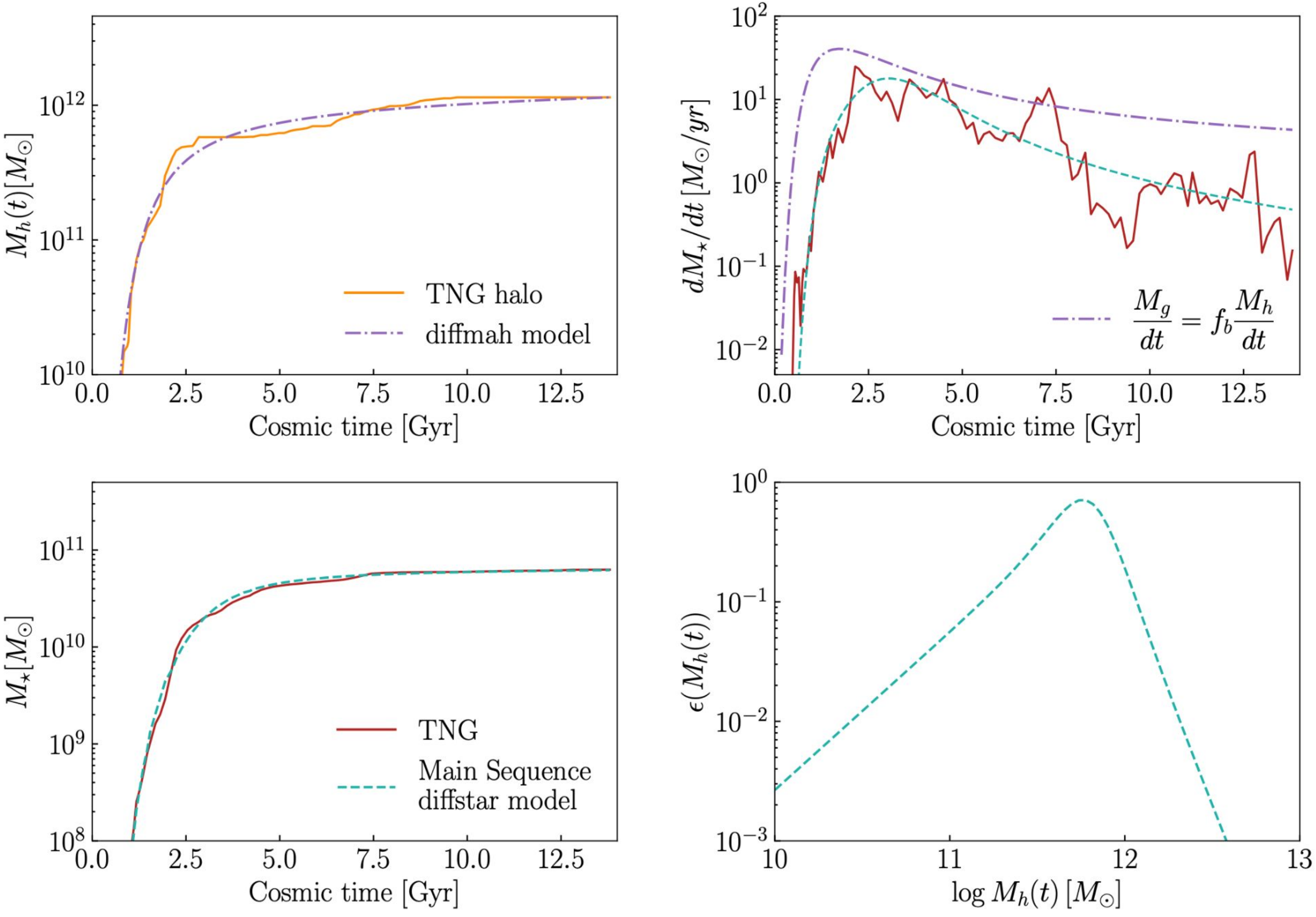
Mass accretion rate

cosmic baryon fraction

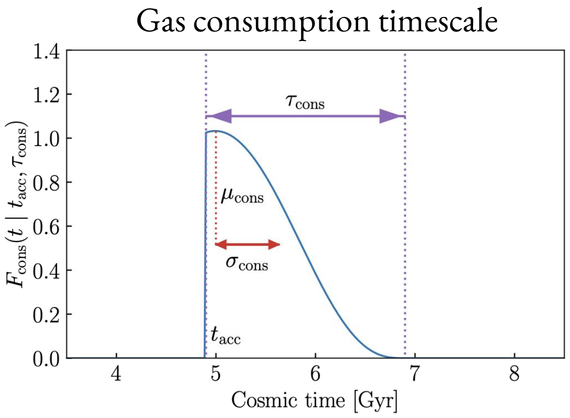


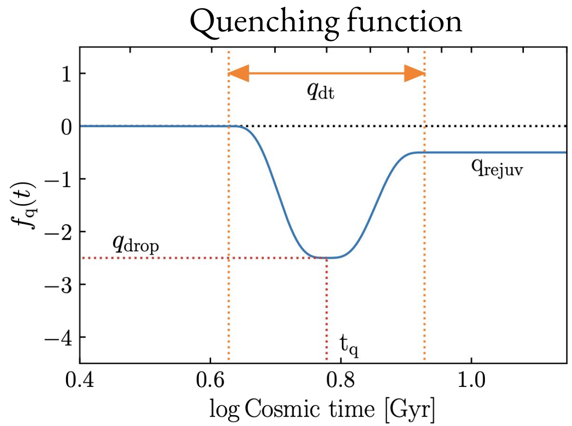
The Diffstar model assumes that only a fraction of the accreted material ever transforms into stars, and that this fraction depends only upon the instantaneous mass of the parent halo.

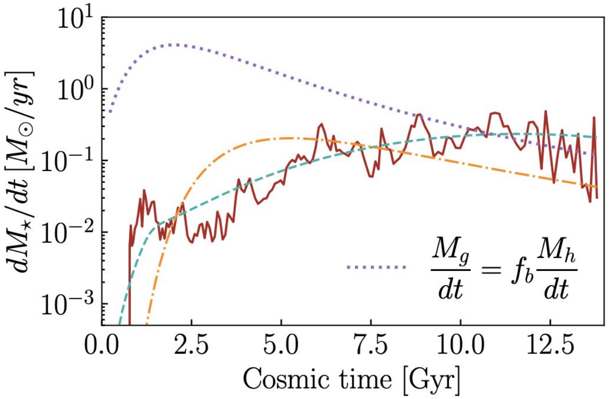


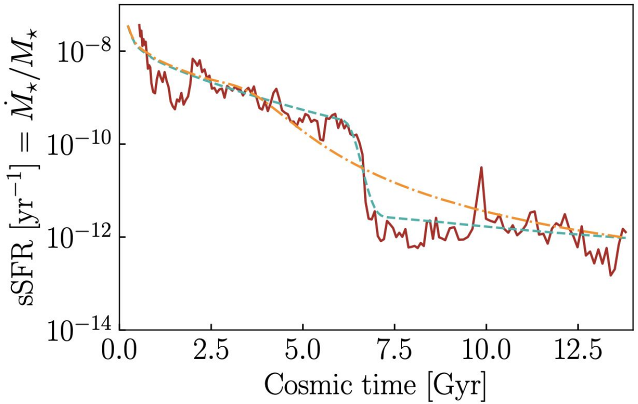

$M_h(t)[M_\odot]$
10^{10}
10^{11}
10^{12}
0.0
2.5
5.0
7.5
10.0
12.5
Cosmic time [Gyr]
TNG halo
diffmah model
$dM_\star/dt\,[M_\odot/yr]$
10^{-2}
10^{-1}
10^{0}
10^{1}
10^{2}
0.0
2.5
5.0
7.5
10.0
12.5
Cosmic time [Gyr]
$\frac{M_g}{dt} = f_b \frac{M_h}{dt}$
$M_\star[M_\odot]$
10^{8}
10^{9}
10^{10}
10^{11}
0.0
2.5
5.0
7.5
10.0
12.5
Cosmic time [Gyr]
TNG
Main Sequence
diffstar model
$\epsilon(M_h(t))$
10^{-3}
10^{-2}
10^{-1}
10^{0}
10
11
12
13
$\log M_h(t)\,[M_\odot]$

Diffstar: Gas consumption and Quenching





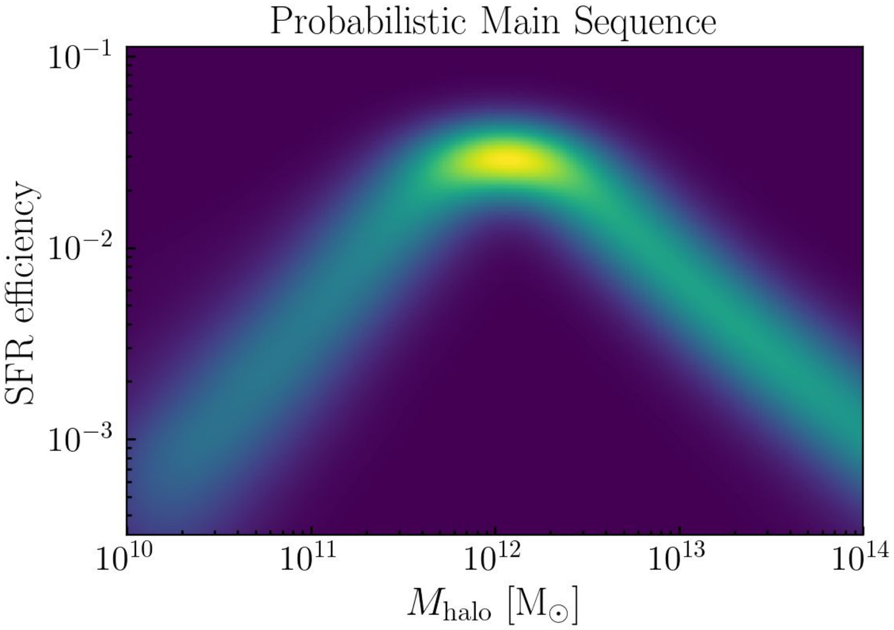




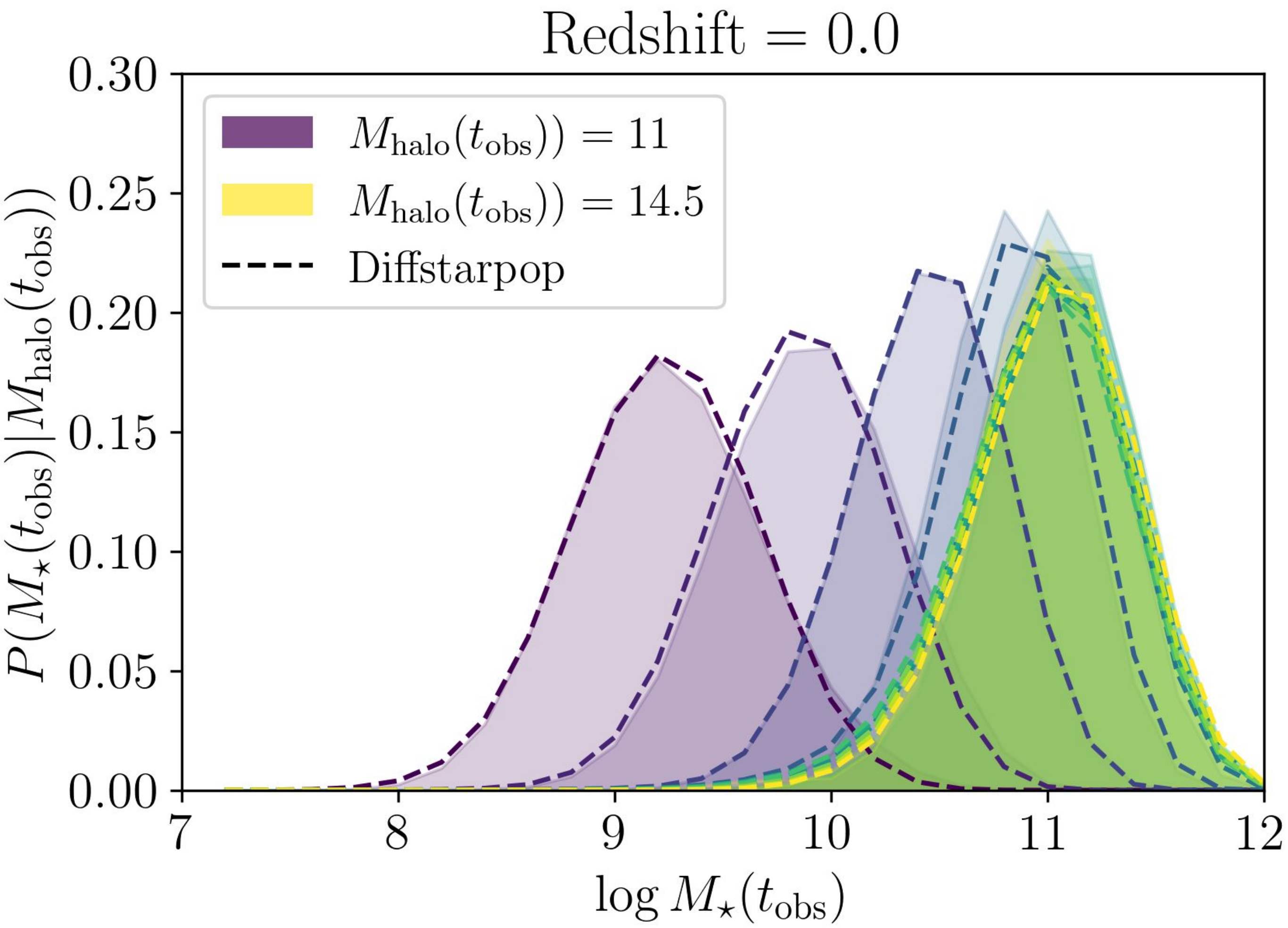
DiffstarPop: Properties of galaxy populations

$$\theta_{\mathrm{SFH}} \rightarrow \mathrm{SFH(t)}$$

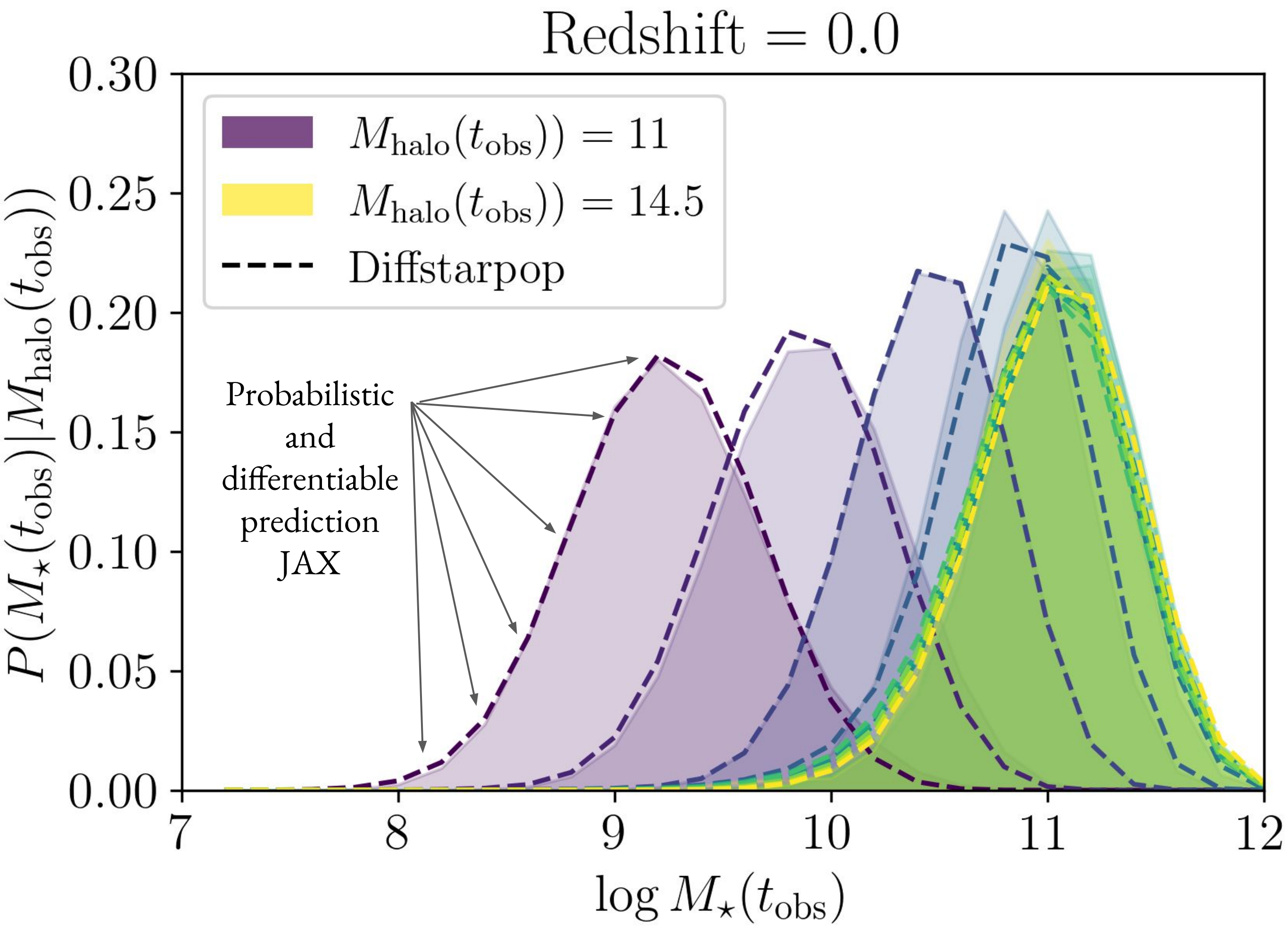
$$\Psi_{\mathrm{SFH}} \rightarrow P(\theta_{\mathrm{SFH}} | \Psi_{\mathrm{SFH}}) \rightarrow P(\mathrm{SFH(t)})$$



Parametrize a *probabilistic* galaxy that lives in each halo



Redshift = 0.0
$M_{\rm halo}(t_{\rm obs})) = 11$
$M_{\rm halo}(t_{\rm obs})) = 14.5$
Diffstarpop
$P(M_\star(t_{\rm obs})|M_{\rm halo}(t_{\rm obs}))$
$\log M_\star(t_{\rm obs})$
0.00
0.05
0.10
0.15
0.20
0.25
0.30
7
8
9
10
11
12



Redshift = 0.0
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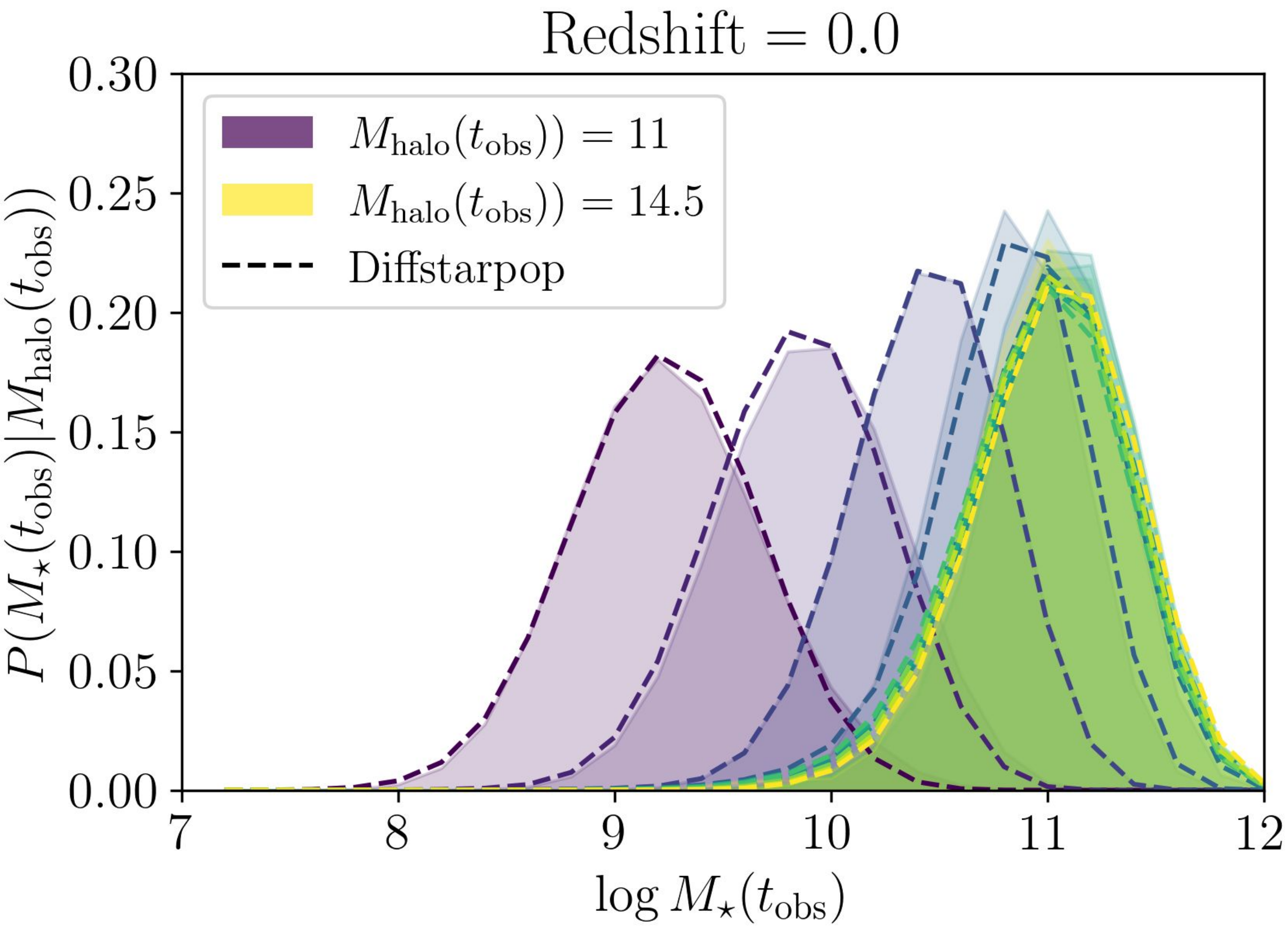
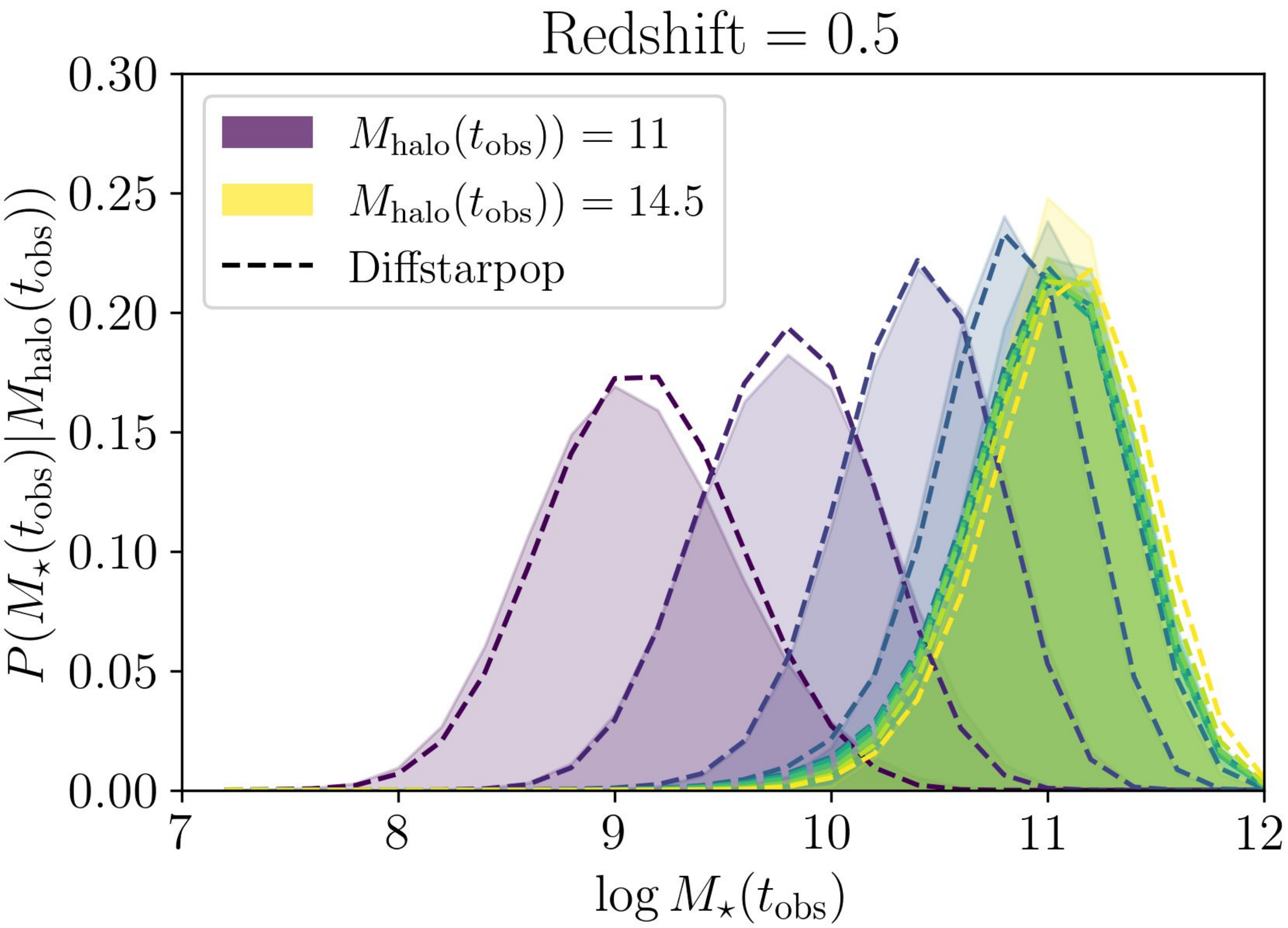
Diffstarpop
Probabilistic and differentiable prediction JAX
$P(M_\star(t_{\rm obs})|M_{\rm halo}(t_{\rm obs}))$
$\log M_\star(t_{\rm obs})$
0.00
0.05
0.10
0.15
0.20
0.25
0.30
7
8
9
10
11
12



Redshift = 0.0
0.30
0.25
0.20
0.15
0.10
0.05
0.00
$M_{\rm halo}(t_{\rm obs})) = 11$
$M_{\rm halo}(t_{\rm obs})) = 14.5$
Diffstarpop
$P(M_\star(t_{\rm obs})|M_{\rm halo}(t_{\rm obs}))$
7
8
9
10
11
12
$\log M_\star(t_{\rm obs})$



Redshift = 0.5
0.30
0.25
0.20
0.15
0.10
0.05
0.00
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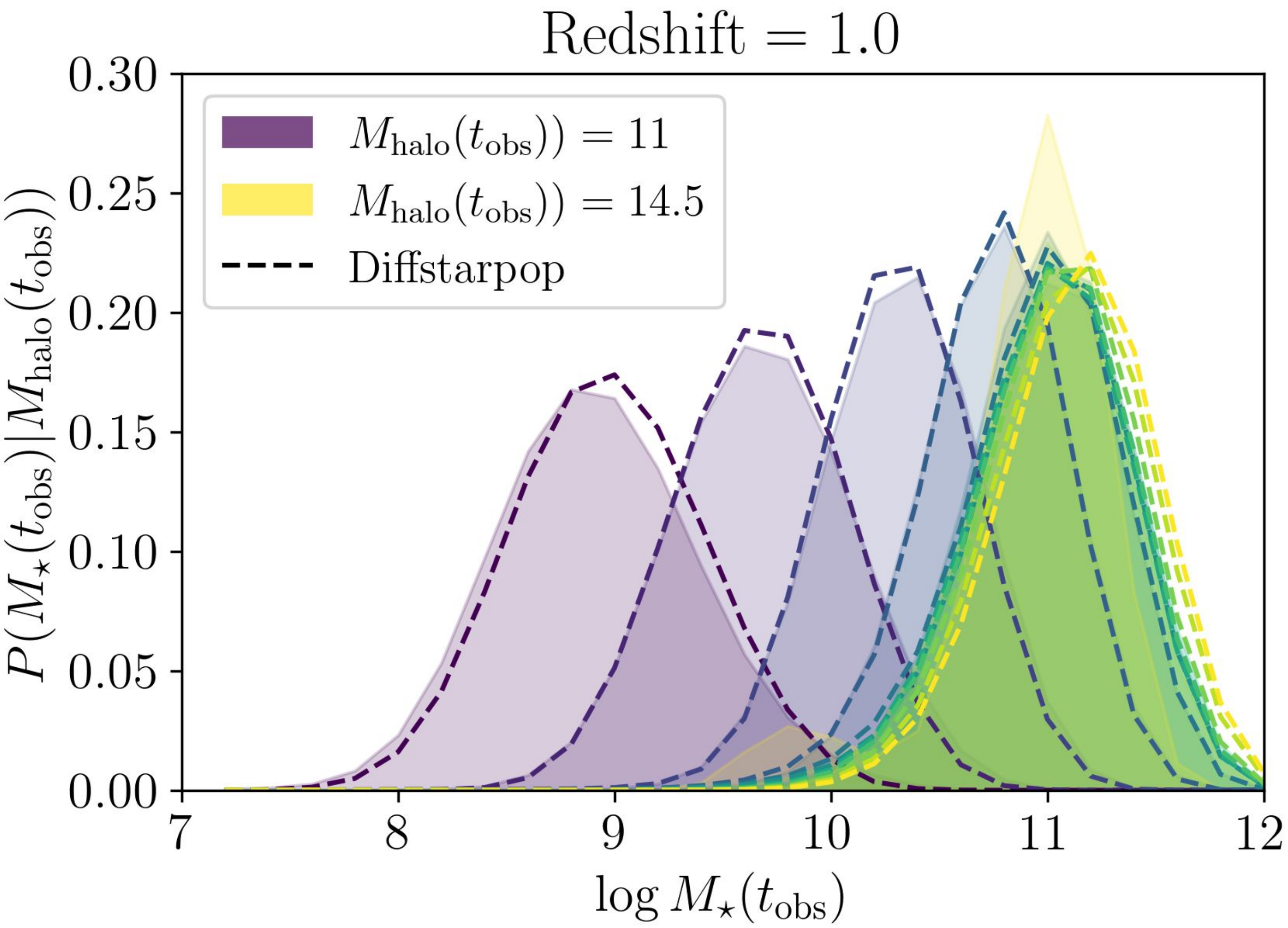
7
8
9
10
11
12
$\log M_\star(t_{\rm obs})$



Redshift = 1.0
$M_{\rm halo}(t_{\rm obs})) = 11$
$M_{\rm halo}(t_{\rm obs})) = 14.5$
Diffstarpop
$P(M_\star(t_{\rm obs})|M_{\rm halo}(t_{\rm obs}))$
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0.00
0.05
0.10
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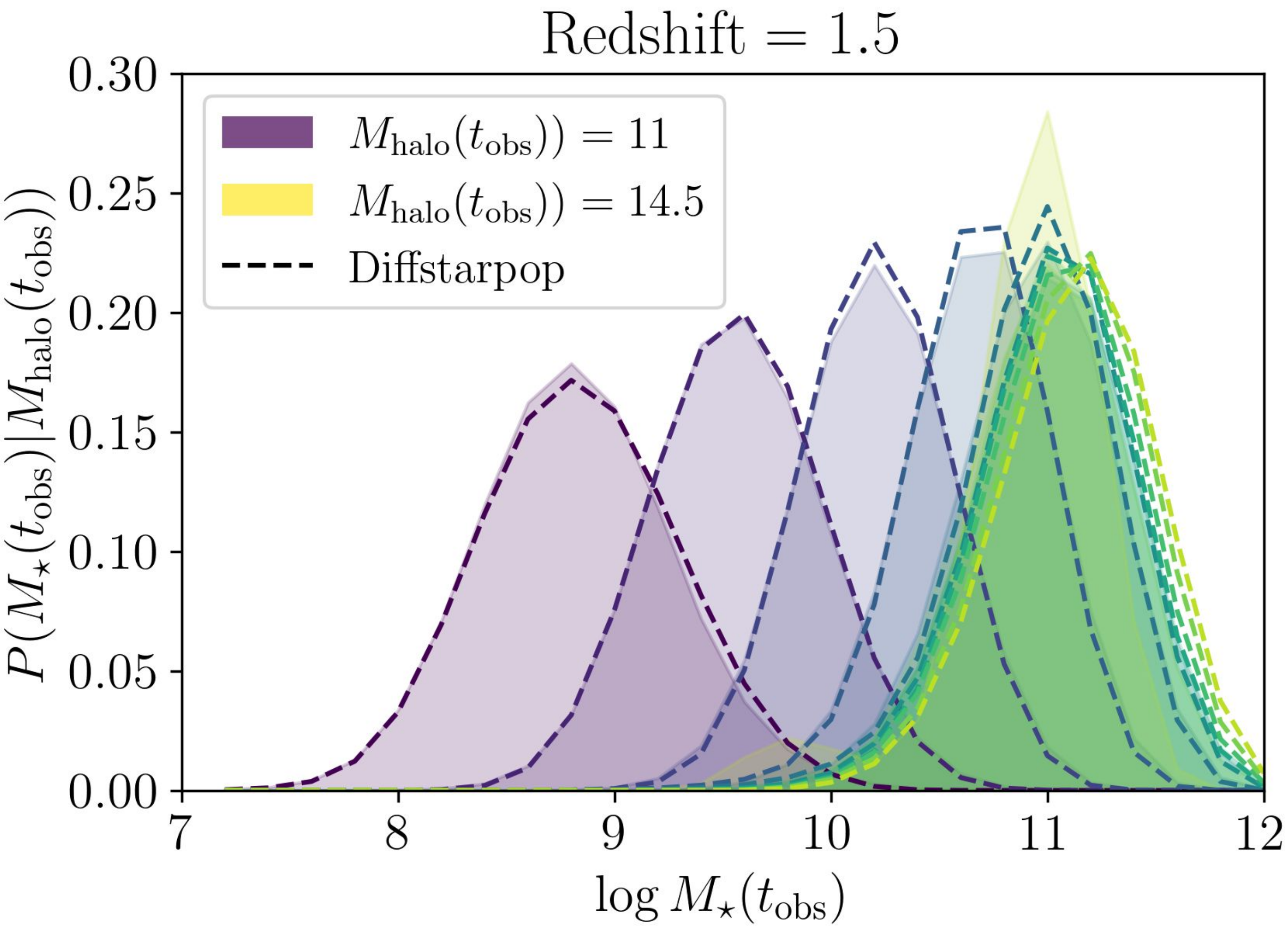
7
8
9
10
11
12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0.00
0.05
0.10
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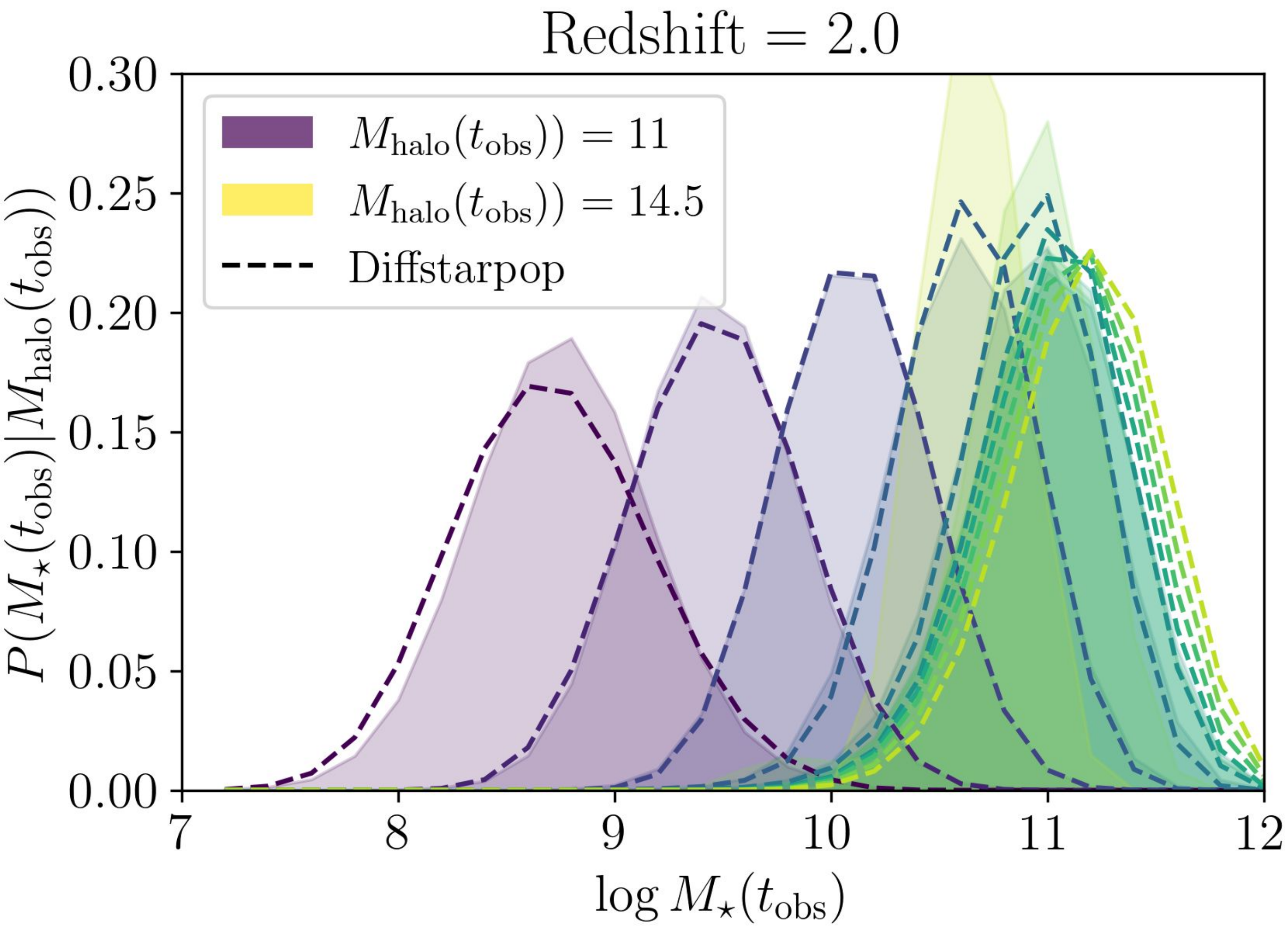
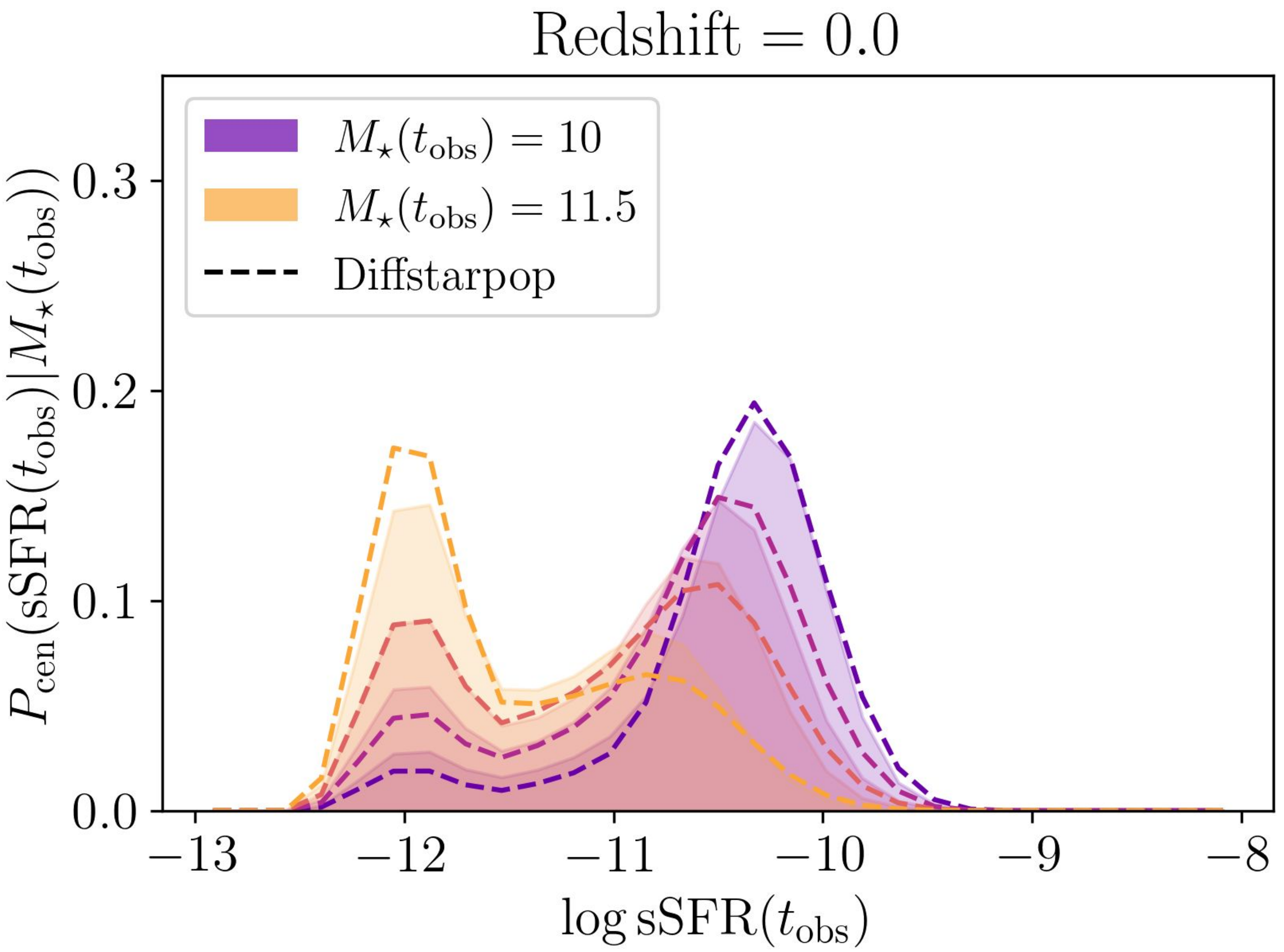
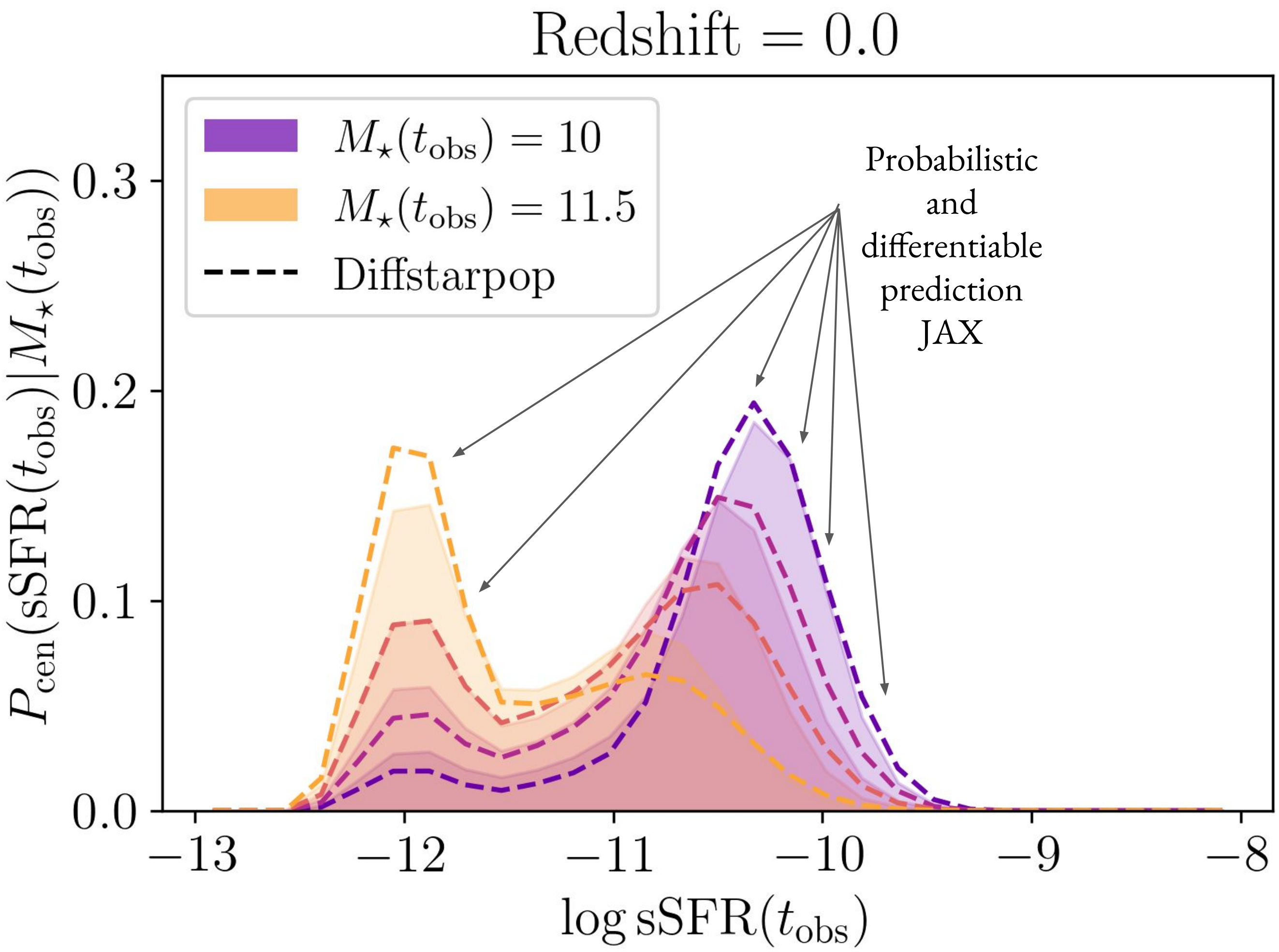
0.25
0.30
7
8
9
10
11
12



Redshift = 2.0
$M_{\rm halo}(t_{\rm obs})) = 11$
$M_{\rm halo}(t_{\rm obs})) = 14.5$
Diffstarpop
$P(M_\star(t_{\rm obs})|M_{\rm halo}(t_{\rm obs}))$
$\log M_\star(t_{\rm obs})$
0.00
0.05
0.10
0.15
0.20
0.25
0.30
7
8
9
10
11
12



Redshift = 0.0
$M_\star(t_{\rm obs}) = 10$
$M_\star(t_{\rm obs}) = 11.5$
Diffstarpop
$P_{\rm cen}(\mathrm{sSFR}(t_{\rm obs})|M_\star(t_{\rm obs}))$
0.0
0.1
0.2
0.3
−13
−12
−11
−10
−9
−8
$\log \mathrm{sSFR}(t_{\rm obs})$



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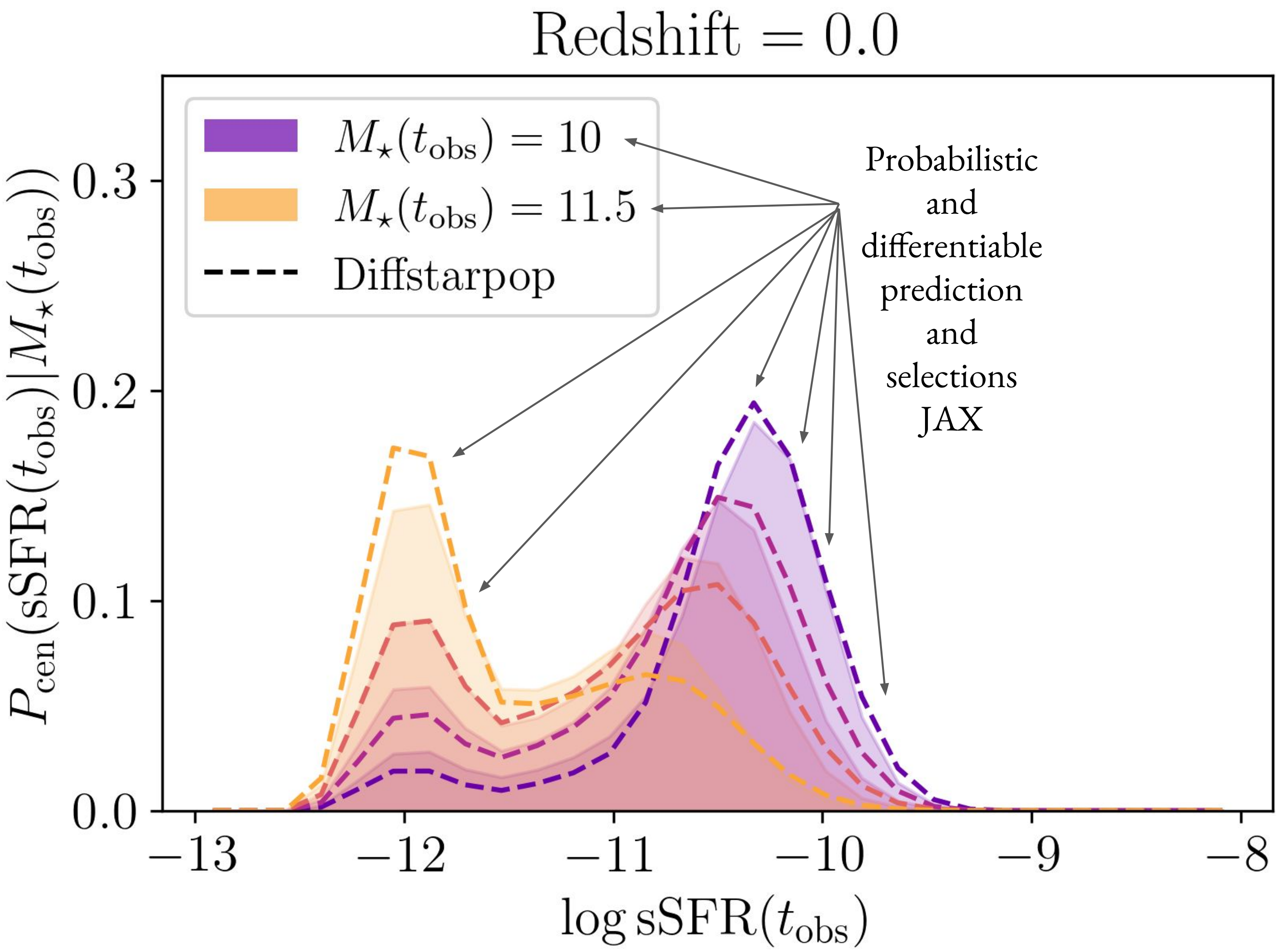
Diffstarpop
Probabilistic
and
differentiable
prediction
JAX
$P_{\rm cen}(\rm sSFR(t_{obs})|M_\star(t_{obs}))$
0.0
0.1
0.2
0.3
−13
−12
−11
−10
−9
−8
$\log \rm sSFR(t_{obs})$



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Diffstarpop
Probabilistic and differentiable prediction and selections JAX
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0.1
0.2
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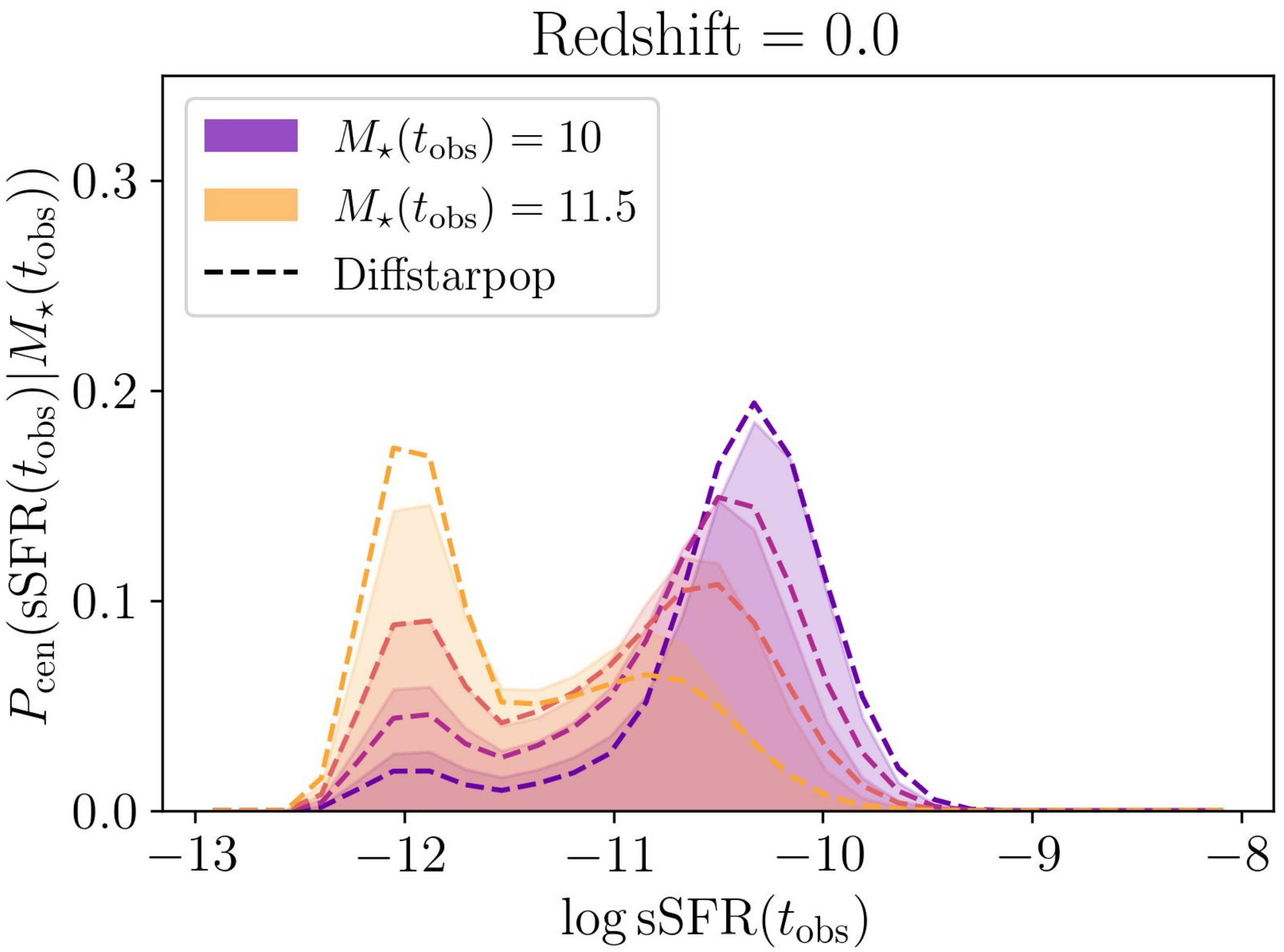
$\log \rm sSFR(t_{obs})$



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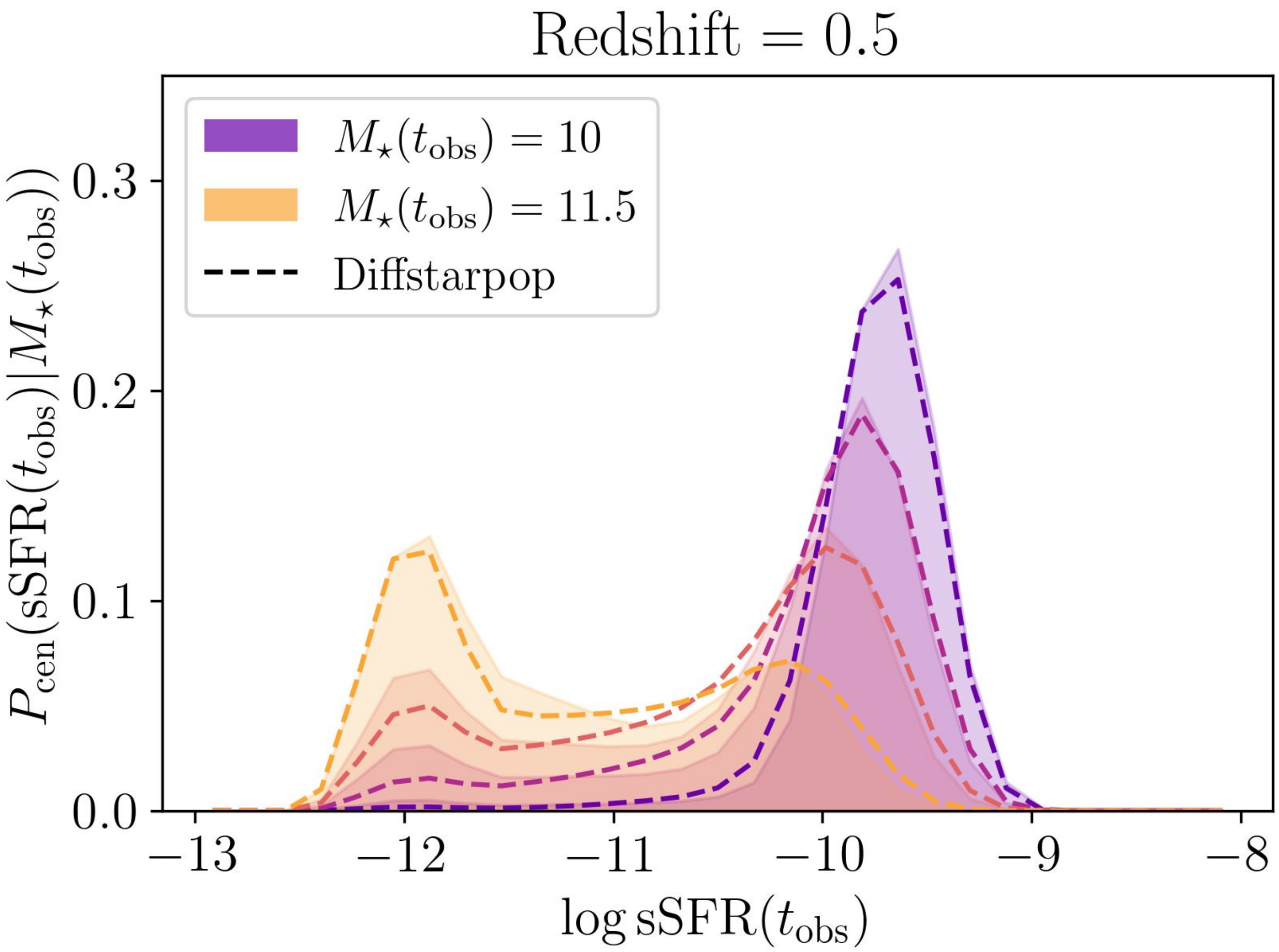

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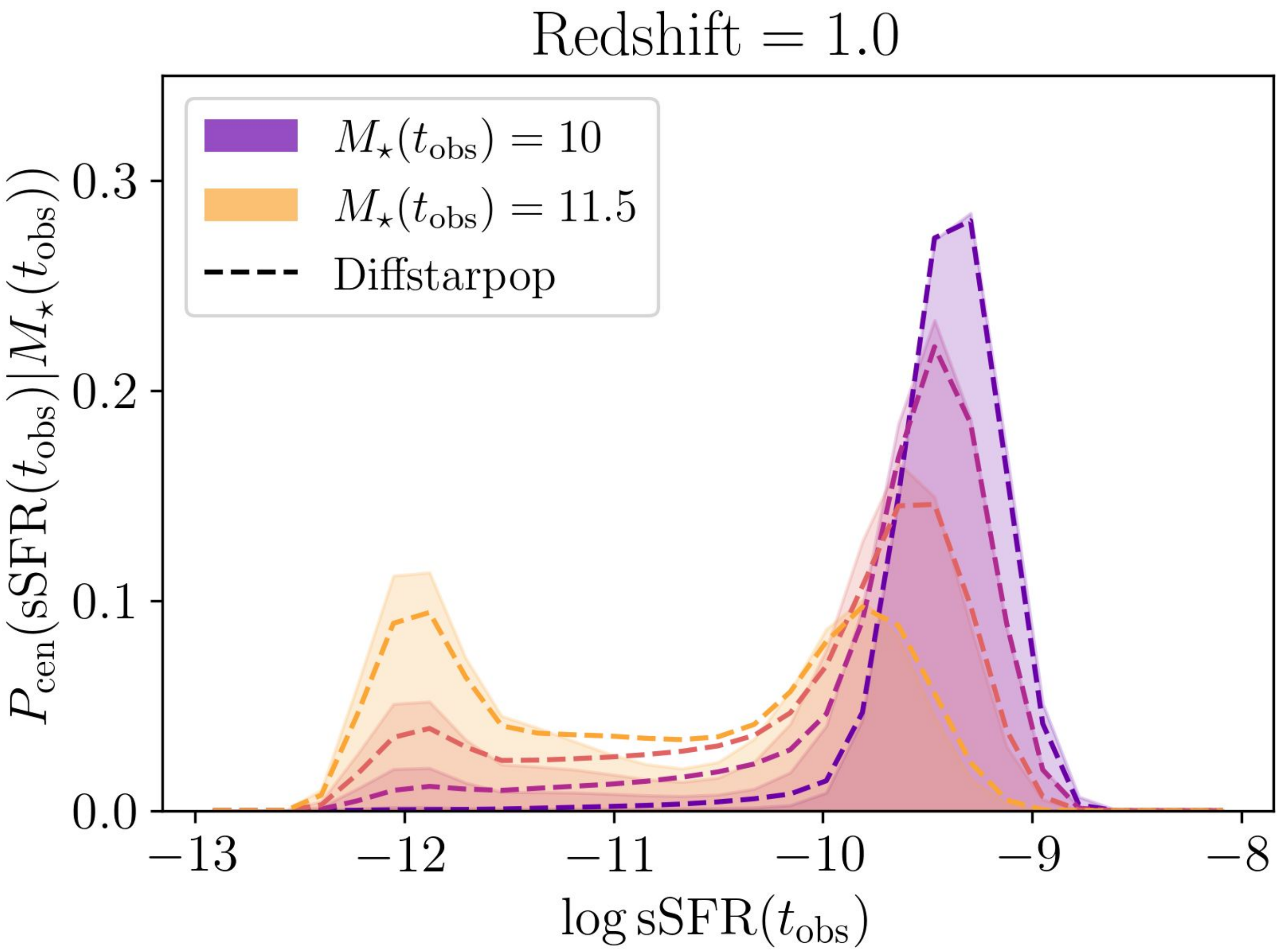
−9
−8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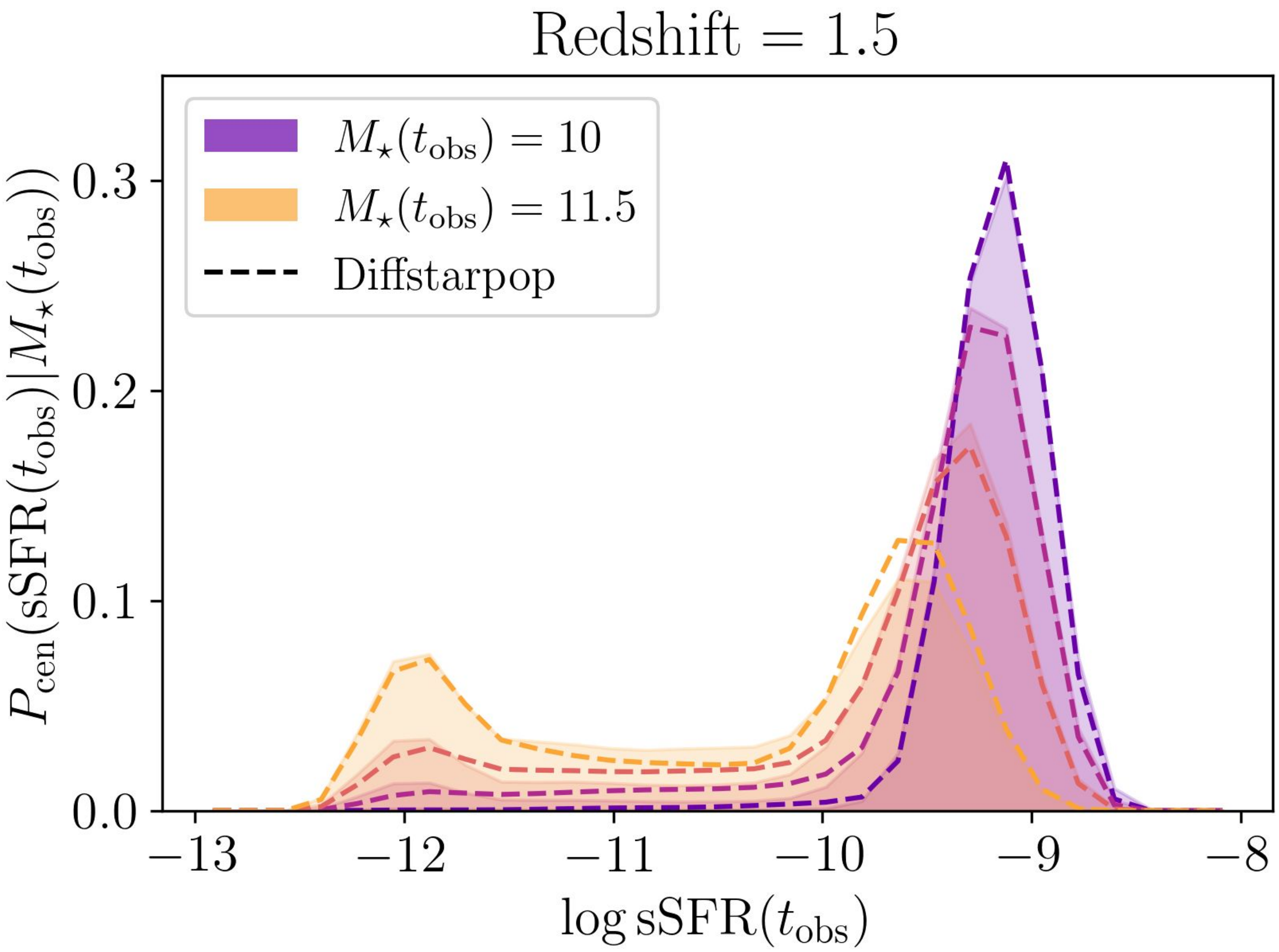
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0.2
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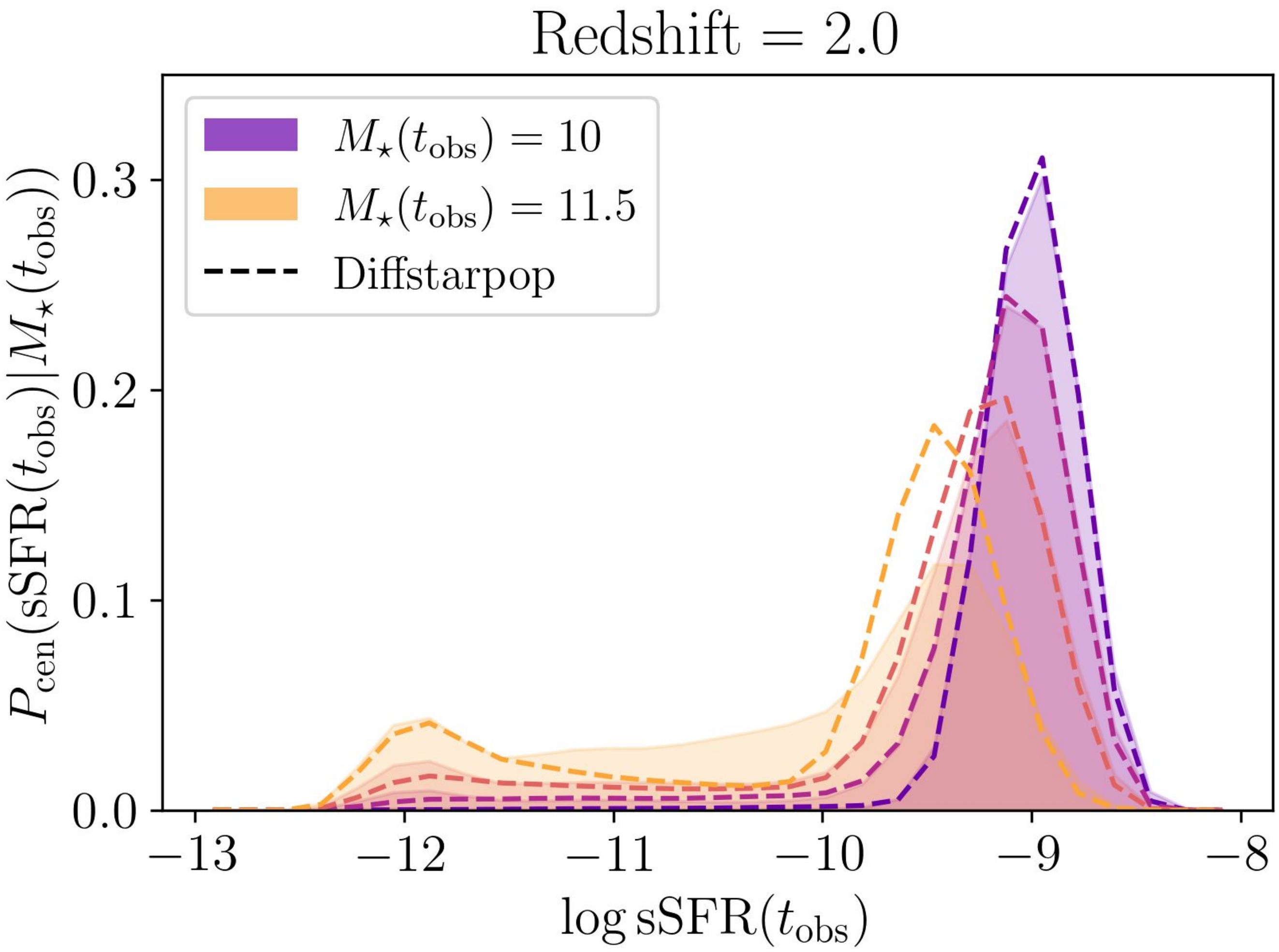
−8
$\log \mathrm{sSFR}(t_{\rm obs})$



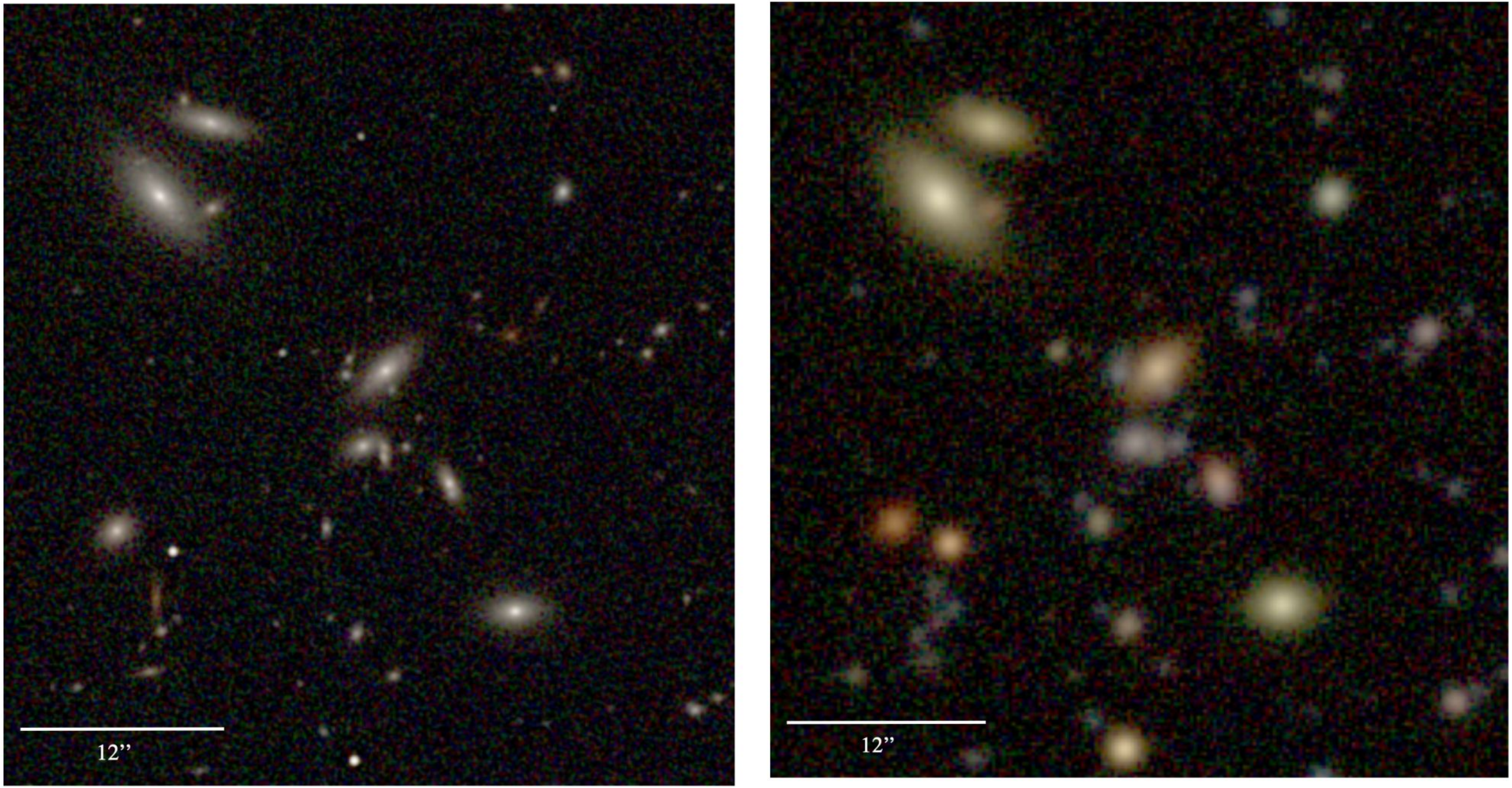
Redshift = 2.0
$M_\star(t_{\rm obs}) = 10$
$M_\star(t_{\rm obs}) = 11.5$
Diffstarpop
$P_{\rm cen}(\rm sSFR(t_{\rm obs})|M_\star(t_{\rm obs}))$
0.0
0.1
0.2
0.3
−13
−12
−11
−10
−9
−8
$\log \rm sSFR(t_{\rm obs})$

First applications using a prototype model

2501.05632
OpenUniverse
PI: Troxel

Roman + LSST image simulations (Galsim) with Outer Rim + prototype Diffsky model)

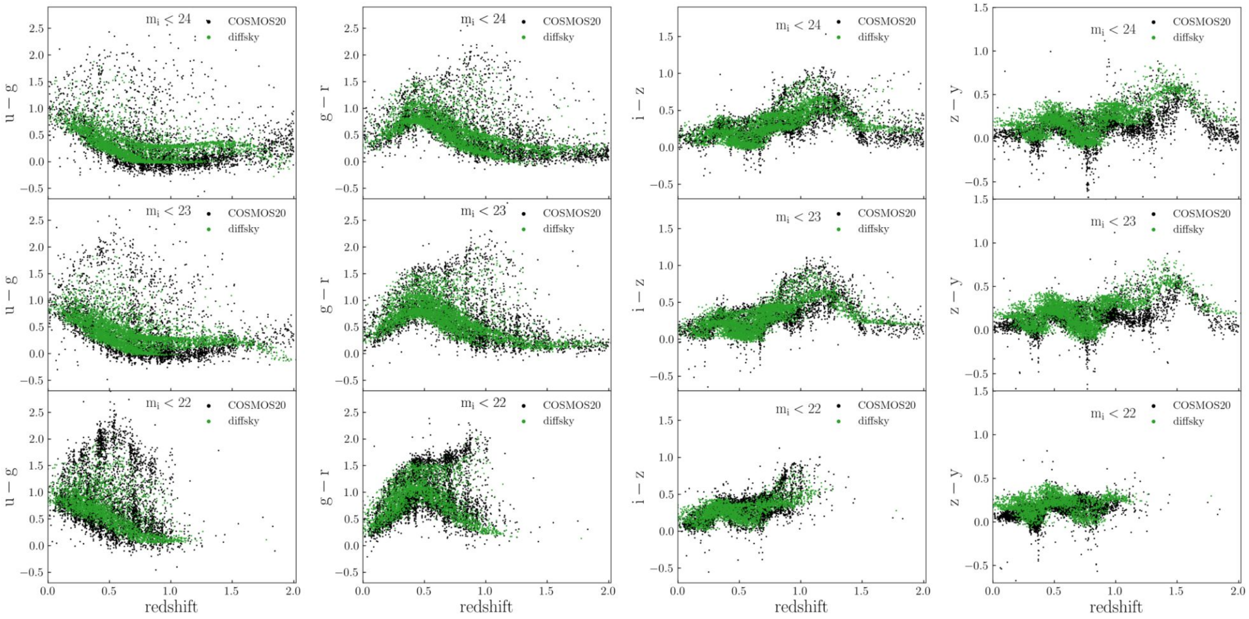
2501.05632



First applications using a prototype model

2501.05632
OpenUniverse
Data access.

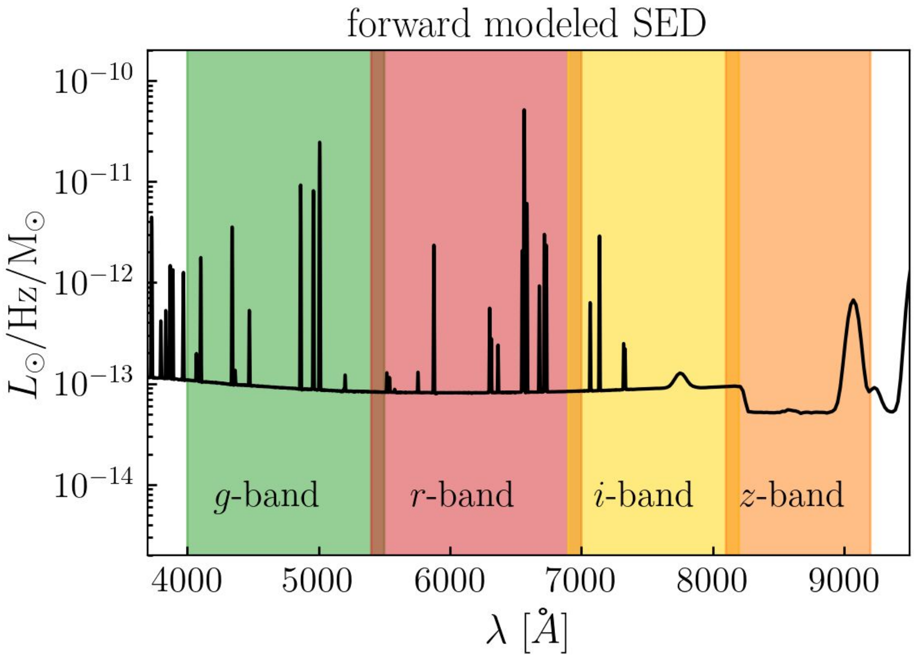
- **Prototype model:**
  - Using a prototype version of Diffsky on SMDPL.
  - Transferring galaxies from SMDPL to Outer Rim by matching on halo properties.



DSPS: Differentiable GPU-Accelerated SEDs/Photometry

DSPS:
2112.06830

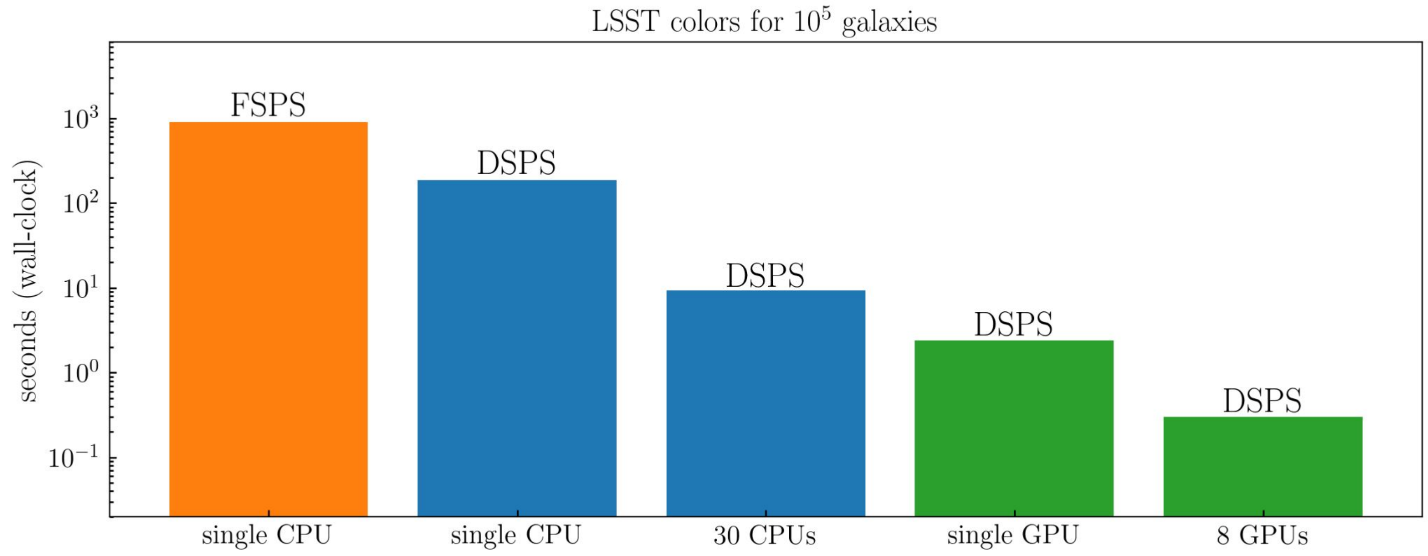
- SPS models include ingredients for dust, bursty star formation, metallicity, etc.



DSPS: Differentiable GPU-Accelerated SEDs/Photometry

DSPS:
2112.06830

- SPS models include ingredients for dust, bursty star formation, metallicity, etc.
- **Enormous performance gains** from DSPS: a JAX-based implementation of SPS



Conclusions

Long term goals:

- Multi-wavelength, same-sky observable predictions.
- Predicting Nonlinear galaxy clustering.
- Predicting Gas fraction + baryonification lensing predictions.
- Predictions for Multiple samples and their cross correlations.
- SED modeling and Redshift Calibration

Additional slides

DiffstarPop: Evolution of galaxy populations

$$\theta_{\mathrm{SFH}} \rightarrow \mathrm{SFH(t)}$$

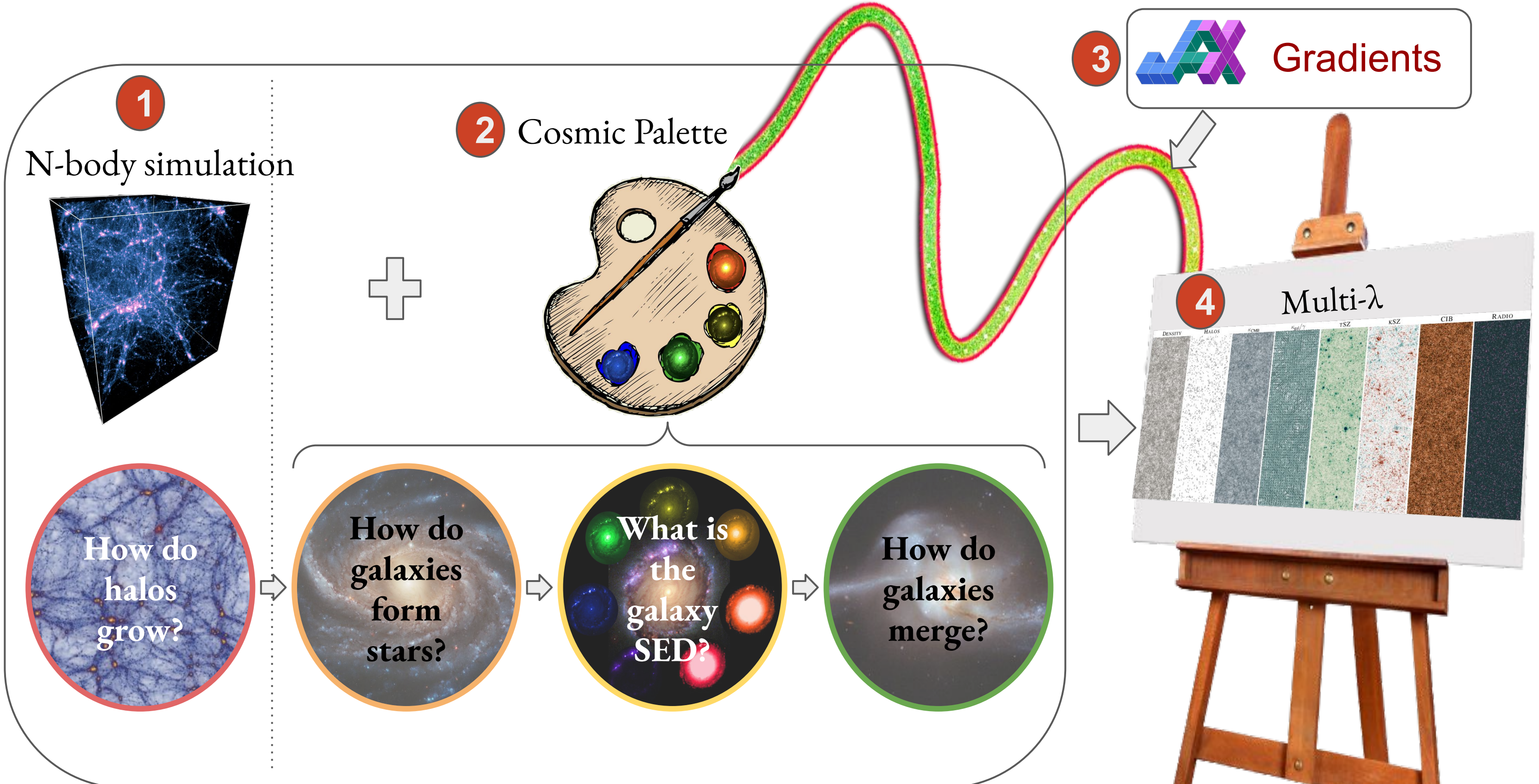
$$\Psi_{\mathrm{SFH}} \rightarrow P(\theta_{\mathrm{SFH}}|\Psi_{\mathrm{SFH}}) \rightarrow P(\mathrm{SFH(t)})$$

Mixture model:

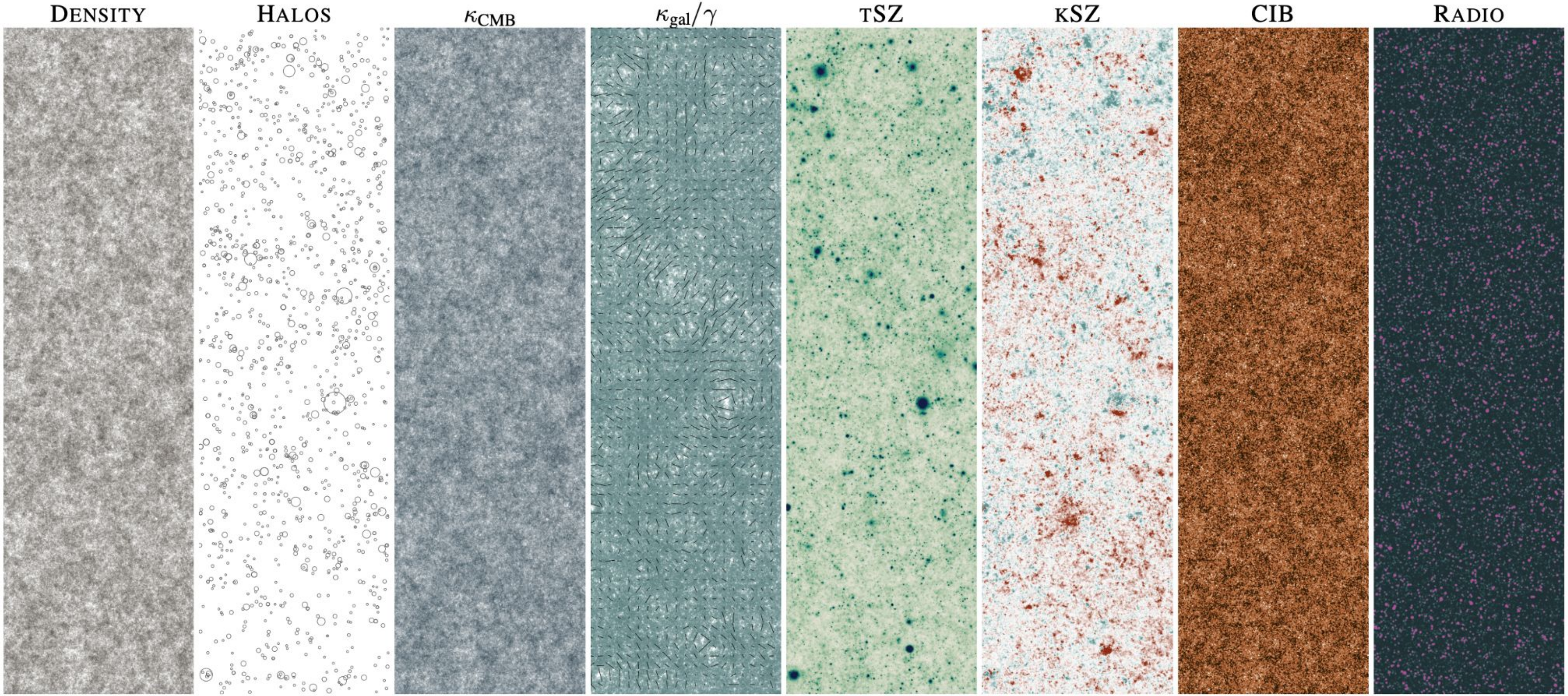
$$P(\theta_{\mathrm{SFH}}|\Psi_{\mathrm{SFH}}) = (1 - f_{\mathrm{quench}}) \overbrace{P_{\mathrm{MS}}(\theta_{\mathrm{SFH}}|\Psi_{\mathrm{MS}})}^{\text{Main sequence galaxies}} + f_{\mathrm{quench}} \overbrace{P_{\mathrm{Q}}(\theta_{\mathrm{SFH}}|\Psi_{\mathrm{Q}})}^{\text{Quenched galaxies}}$$

Linear scaling relations of each parameter with present-day halo mass M_0.

Applications: Differentiable Sky Predictions



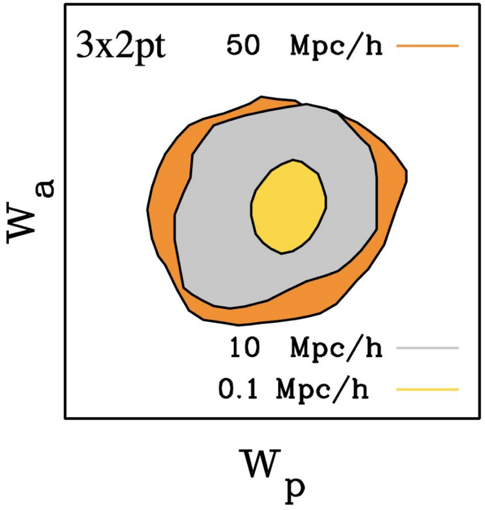
Burgeoning amount of multi-λ observations

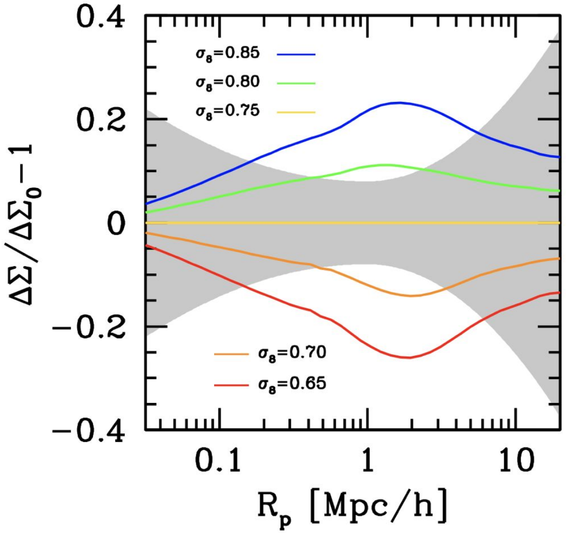


Yuuki Omori/Agora simulation

Large-scale structure in the non-linear regime

- Significant predicted cosmological gains by going to smaller scales.

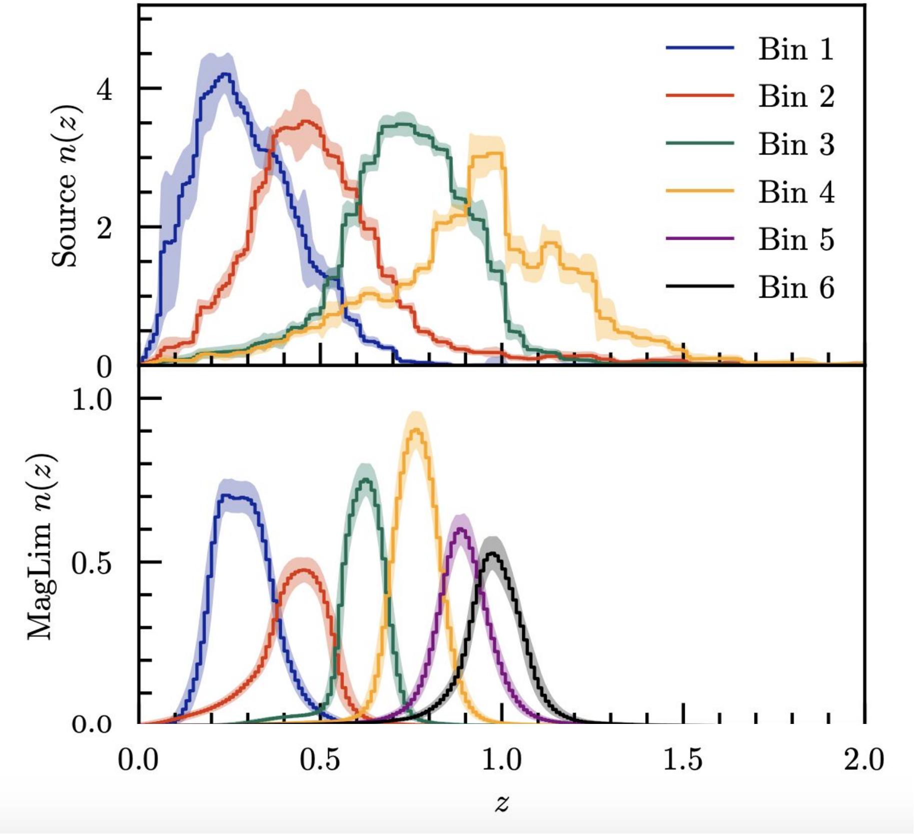




1804.03097

Overlap between galaxy samples

- Simultaneous forward modeling of auto- and cross-correlations of galaxy samples.
- Forward modeling of galaxy sample selections.
- Modeling the contributions of different parts of the sample to each correlation function.



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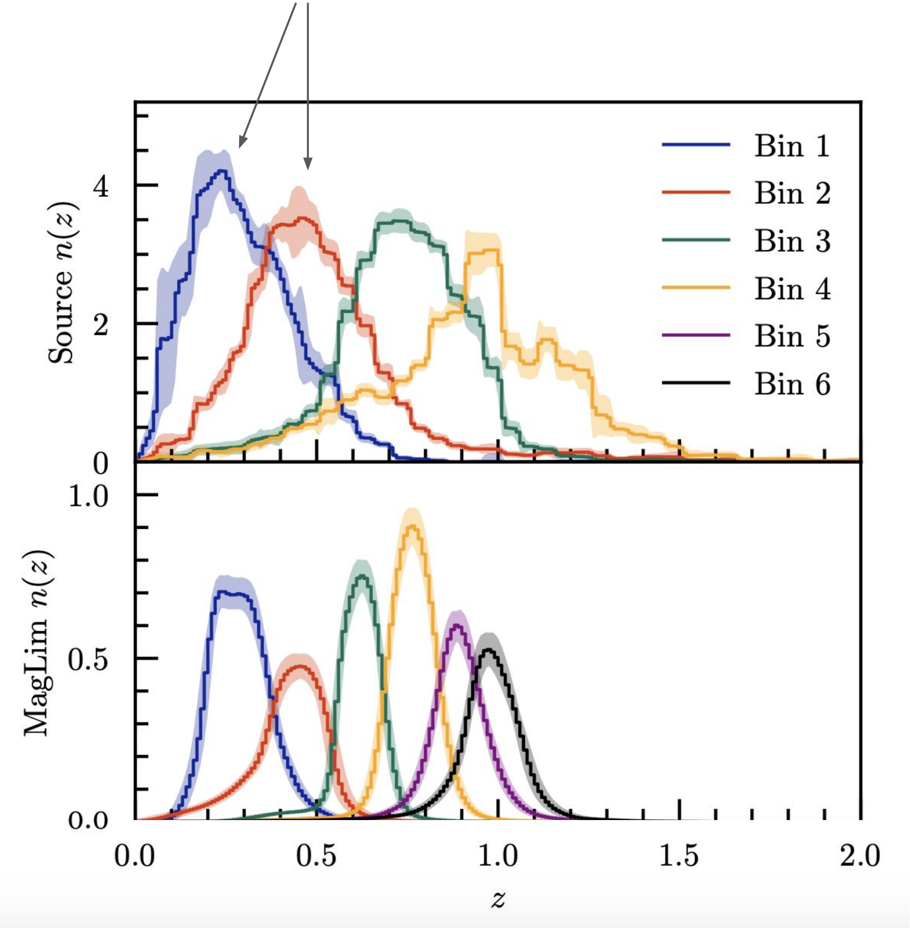

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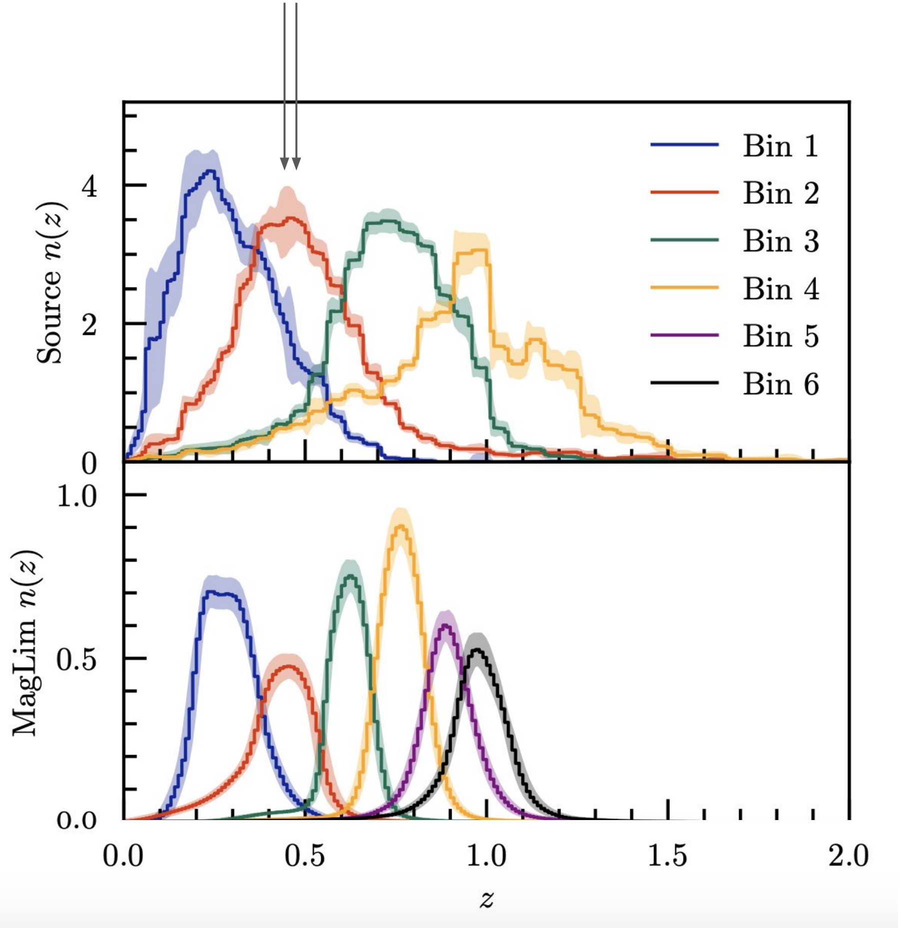

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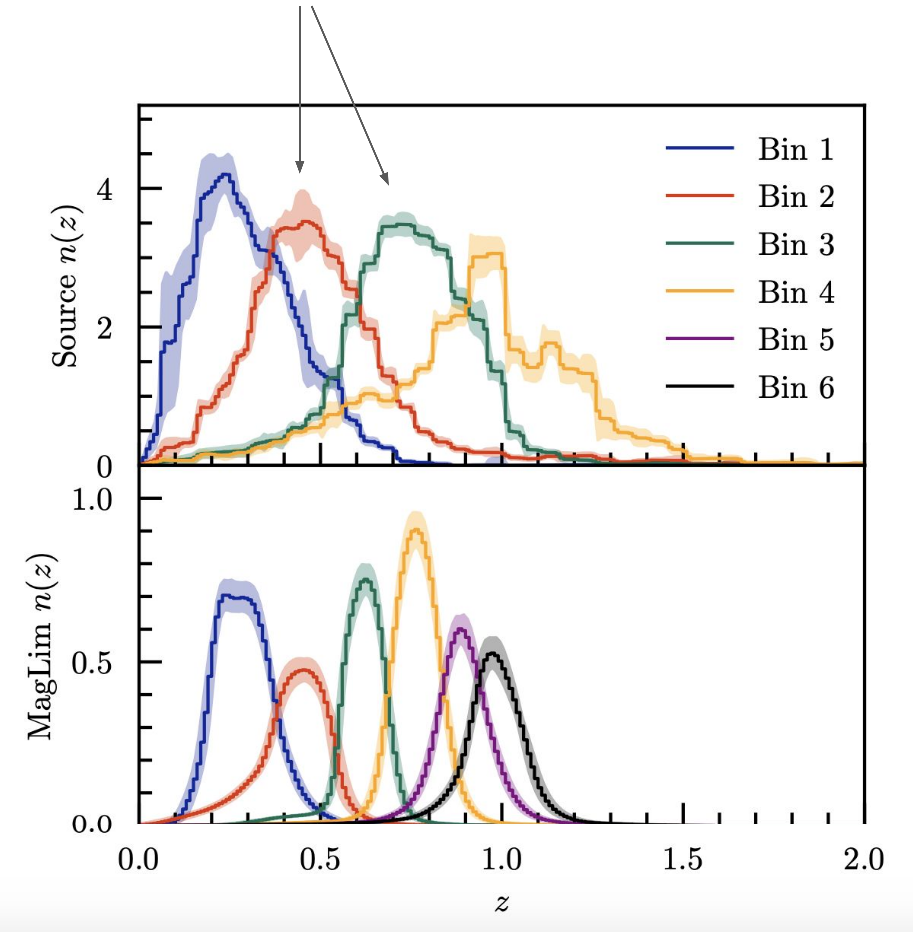
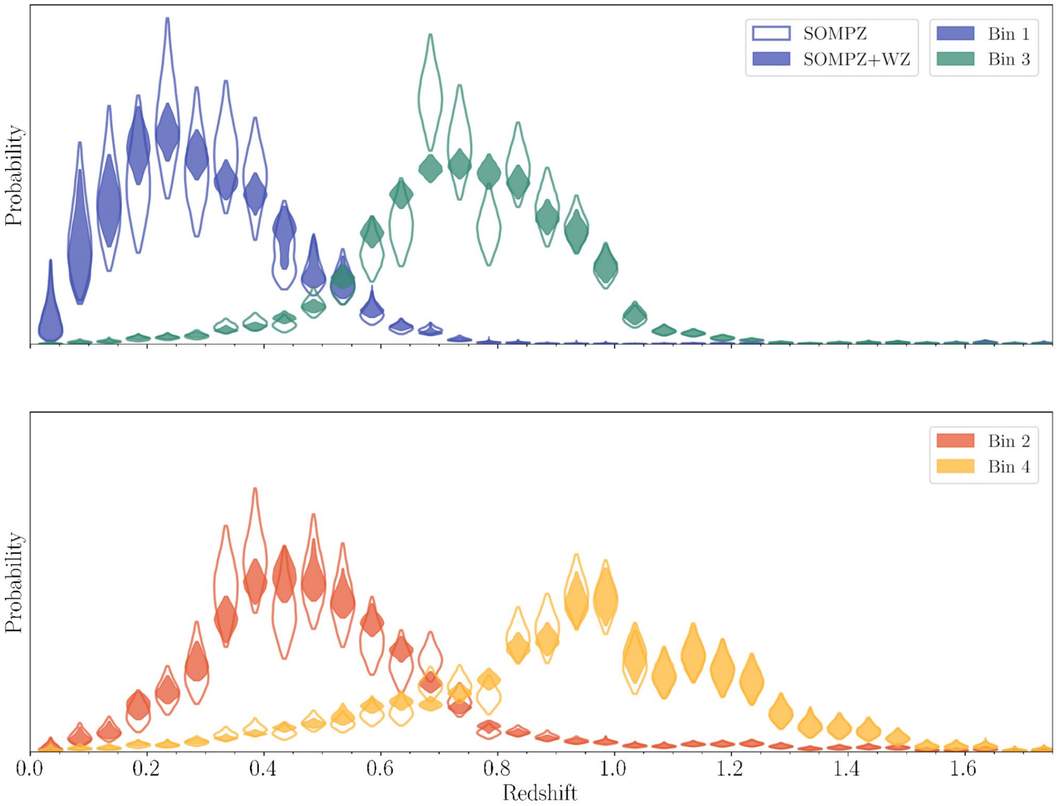


Applications: Redshift calibration for Weak Lensing surveys

- Can we use the galaxy-halo connection to improve redshift calibration in photometric weak lensing surveys.
- Differentiable galaxy SED modeling.
- Physical priors inspired by models of galaxy formation.
- Hierarchical Bayesian model.
- Challenges from combining heterogeneous data (Euclid + LSST).



Applications: Redshift calibration for Weak Lensing surveys

Goal: Reducing the uncertainty in the accuracy of the mean redshift of galaxy samples.

Reality:

- DES ~ 0.013 (i~23.8)
- KiDs ~ 0.010 (i~23.5)
- HSC ~ 0.030 (i~24.5)

Upcoming requirements:

- LSST ~ 0.002 (1+z) in Y1 and 0.001 (1+z) by Y10.
- Euclid ~ 0.002 (1+z) in accuracy, 0.05(1+z) in precision.

Conclusions

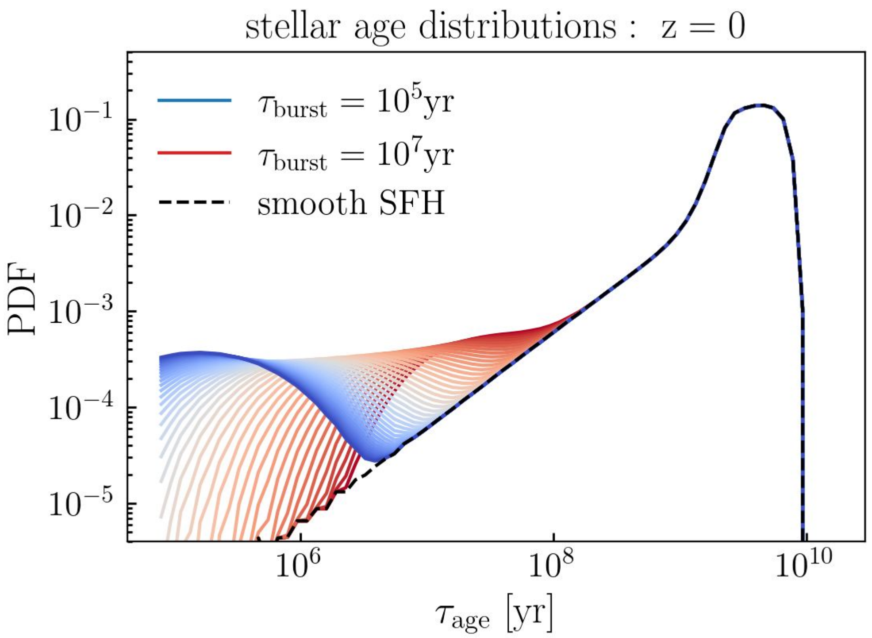
Next steps in Diffstarpop:

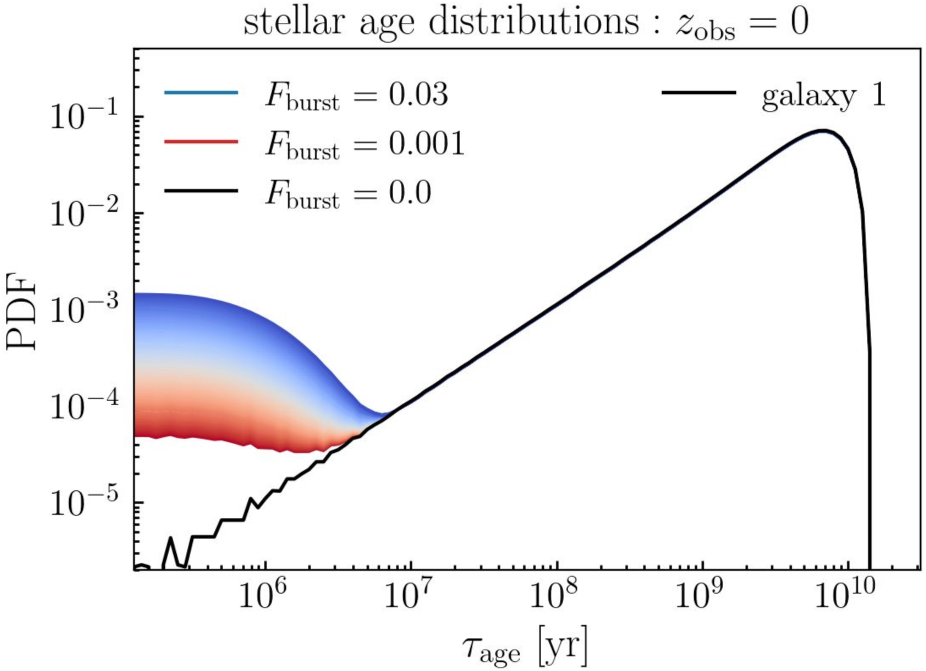
- Adding satellite specific quenching.
- Predicting galaxy assembly bias effects.
- Combining with galaxy merging: ex-situ stellar mass.

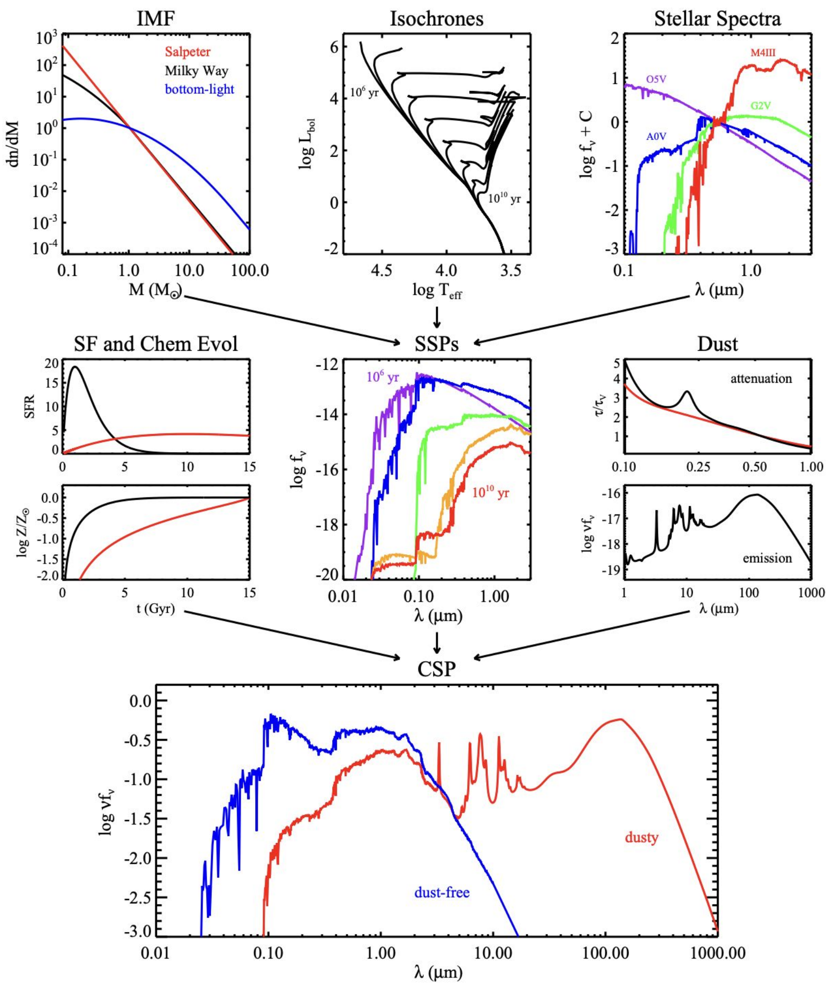
Exciting future applications:

- Multi-λ same-sky observable prediction.
- Non-linear galaxy clustering.
- Multi-sample observable prediction.
- SED modeling and Redshift Calibration

Diffburst Model of short-timescale SFH(t)







IMF
Salpeter
Milky Way
bottom-light
dn/dM
M (M⊙)
Isochrones
10^6 yr
10^10 yr
log L_bol
log T_eff
Stellar Spectra
M4III
O5V
G2V
A0V
log f_ν + C
λ (μm)
SSPs
10^6 yr
10^10 yr
log f_ν
λ (μm)
SF and Chem Evol
SFR
log Z/Z⊙
t (Gyr)
Dust
attenuation
τ/τ_V
emission
log νf_ν
λ (μm)
CSP
log νf_ν
dusty
dust-free
λ (μm)